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ABSTRACT

Modeling International Diffusion: Inferential Benefits and Methodological Challenges, with an Application to International Tax Competition

by Robert J. Franzese, Jr. and Jude C. Hays

Although scholars recognize that time-series-cross-section data typically correlate across both time and space, they tend to model temporal dependence directly, often by lags of dependent variables, but to address spatial interdependence solely as a nuisance to be "corrected" by FGLS or to which to be "robust" in standard-error estimation (by PCSE). We explore the inferential benefits and methodological challenges of directly modeling international diffusion, one form of spatial dependence. To this end, we first identify two substantive classes of modern *comparative-and-international-political-economy (C&IPE)* theoretical models—*(context-conditional) open-economy comparative political-economy (CPE)* models and *international political-economy (IPE)* models, which imply diffusion (along with predecessors, *closed-economy CPE* and *orthogonal open-economy CPE*)—and then we evaluate the relative performance of three estimators—*non-spatial OLS*, *spatial OLS*, and *spatial 2SLS*—for analyzing empirical models corresponding to these two modern alternative theoretical visions from spatially interdependent data. Finally, we offer a substantive application of the *spatial 2SLS* approach in what we call a *spatial error-correction model* of international tax competition.

Keywords: International Tax Competition, Panel Models, Policy Diffusion, Political Economy, Spatial Interdependence

JEL Classification: C23, H20

ZUSAMMENFASSUNG

Modellieren von Internationaler Diffusion:
Methodologische Herausforderungen, Vorteile für Schlussfolgerungen und eine Anwendung auf den internationalen Steuerwettbewerb

Obwohl Wissenschaftler wissen, dass Zeitreihenquerschnittsdaten sowohl über die Zeit als auch über den Raum korreliert sind, neigen sie dazu, die zeitliche Abhängigkeit direkt zu modellieren, z. B. durch Zeitabstände der abhängigen Variablen. Die räumliche Abhängigkeit jedoch wird als ein Ärgernis angesehen, welches durch *FGLS* ‚korrigiert' wird oder ‚robust' gemacht wird in Standard-Abweichungs-Schätzungen (durch PCSE). Wir untersuchen methodologische Herausforderungen und die Nutzen für Schlussfolgerungen aus einer direkten Modellierung internationaler Diffusion als einer Form der räumlichen Abhängigkeit. Zu diesem Zweck identifizieren wir zuerst zwei inhaltliche Hauptklassen theoretischer Modelle der modernen ‚Vergleichenden und Internationalen Politischen Ökonomie", nämlich Modelle der (kontextbezogenen) Vergleichenden Politischen Ökonomie Offener Volkwirtschaften und Modelle der Internationalen Politischen Ökonomie. Diese bilden Diffusion ab, ebenso wie die Vorläufermodelle der Vergleichenden Politischen Ökonomie geschlossener Volkswirtschaften und gegensätzlich offener Volkswirtschaften. Zweitens bewerten wir die relative Performanz von drei Schätzern – nicht-räumliche OLS, räumliche OLS und räumliche 2SLS. Schließlich wenden wir den Ansatz des räumlichen 2SLS in einem von uns so genannten ‚Spatial Error Correction'-Modell des internationalen Steuerwettbewerbs an.

Introduction

Although scholars recognize that time-series-cross section data typically correlate across time and space, they tend to treat temporal and spatial interdependence differently. Most analysts model temporal dynamics directly, often by lagging the dependent variable, but address spatial dependence solely by panel-corrected standard-errors or Parks' procedure (feasible generalized-least-squares: FGLS), thereby treating it as a *nuisance* (Ward and O'Loughlin 2002 and Hoff and Ward 2004 may evidence a recent change). We explore the inferential benefits and methodological challenges of directly modeling international diffusion, one form of spatial interdependence.[1]

We begin by identifying three approaches to comparative and international politics and political economy (PE) that motivate distinct empirical models. In closed-economy comparative politics (CP) and comparative political-economy (CPE), the focus is on domestic variables and external shocks and international diffusion processes are ignored.[2] In open-economy CP and CPE, by contrast, the importance of external conditions/shocks (e.g., oil prices) for the domestic political-economy is recognized; but the domestic policy or outcome responses to these foreign shocks, which responses may be either moderated by domestic variables (context-conditional open-economy CPE) or unconditioned by domestic variables (orthogonal open-economy CPE), are treated as isolated phenomena. That is, in

[1] Although we follow the common terminology of *spatial* dependence, shocks, *etc.*, whose connotation of *geographic* and *spatial-distance* bases for interdependence (spatial proximity, shared borders, *etc.*) originates from the spatial-econometrics literature's development in geographically related sciences, the notions of *space* and *spatial* dependence extends intuitively to encompass alternative bases of "proximity" that may induce interdependence such as, *e.g.*, economic notions of nearer and further competitors, sociological notions of network connectivity, or socio-political notions of shared or nearer or further *cultural, religious, linguistic, or political heritage*.

[2] Following recent practice in political science, we refer to processes by which the outcomes in some units directly affect the outcomes in other units as *diffusion*. We distinguish such diffusion processes, which will induce *spatial correlation*, from *spatially correlated responses (outcomes) to spatially correlated exogenous shocks*, or *common shocks* for short, which will also induce *spatial correlation*. For us, synonyms for *diffusion* include *contagion*, *strategic interdependence, strategic dependence*; and synonyms for *spatial correlation* include *spatial dependence, interdependence.* We have noticed, however, no consistency within or across disciplines in how these terms are used. For example, *contagion* would be synonymous with *diffusion* specifically in much of biometrics whereas it is often synonymous with *spatial correlation* generally in much of econometrics, and it seems equally likely to mean either in sociology.

open-economy CP and CPE, external shocks affect domestic policies and outcomes, but these domestic policies and outcomes do not themselves affect the policies and outcomes of other units and so do not reverberate throughout the global polity or political economy. Finally, international-relations (IR) scholars and international political economists (IPE) focus explicitly on spatial linkages and mechanisms of diffusion in the global polity and political economy whereby policies and outcomes in some units directly affect the policies and outcomes of other units, perhaps in addition to the possibility that multiple units are exposed to common (or correlated) external shocks. A country might respond to an exogenous domestic or global political or economic shock by lowering its capital tax-rate, for example, but the magnitude of its response may depend on how its competitors respond and, conversely, its own response may affect the capital tax-rates that policymakers in other countries choose. If these responses are competitive, the initiating country will likely lower its capital taxes by more than it would have in the absence of tax competition.

In this paper, we focus on the models of context-conditional open-economy CP/CPE and IR/IPE and methods estimating such models. We do not consider purely domestic models except to note that, if external influences are important, these models will, even in the best of circumstances, produce inefficient estimates of the coefficients for domestic variables and, in the worst, biased and inconsistent estimates. The central problem we consider is the difficulty distinguishing *common shocks* from *international diffusion*. On the one hand, ignoring diffusion processes when they are present will lead analysts to exaggerate the importance of external shocks. On the other hand, if certain endogeneity problems discussed below are insufficiently addressed, modeling diffusion with spatial lags can lead analysts to overestimate the importance of diffusion at the expense of common shocks, especially insofar as such common shocks are inadequately modeled. A spatial two-stage-least-squares estimator seems to provide an effective resolution to this dilemma, at least under the circumstances so far considered: namely, that domestic explanatory variables are not themselves endogenous to dependent variables and are spatially correlated but are not themselves subject to a diffusion process (*i.e.*, they correlate by the *common shocks* mechanism).

We organize the paper as follows. The next section discusses the three approaches to political economy described briefly above, each of which motivates its own characteristic empirical models. The third section presents a generic spatial lag model—an empirical framework well-suited to testing hypotheses about international diffusion—and outline various methods for estimating coefficients in such models. The fourth section details the design of our Monte Carlo experiments, and the fifth presents our results. We conclude these preliminary methodological explorations with discussion of areas where further research is needed, followed in subsequent sections by a substantive example application to a spatial error-correction model of international tax competition.

Comparative Political Economy vs. International Political Economy[3]

Over the development of substantive political economy *(PE)* as a field of inquiry, one can distinguish four broad visions of comparative and international political economy *(C&IPE)*: closed-economy comparative-political-economy *(C-CPE)*, orthogonal open-economy CPE *(O-O-CPE)*, context-conditional open-economy CPE *(CC-O-CPE)*, and (comparative and) international political economy *((C&)IPE)*, which last implies diffusion/strategic-interdependence. Each of these broad visions of PE has a characteristic mathematical expression of its empirical implications, and these characteristic empirical specifications clarify the inherent theoretical stance (assumption) in each regarding the substantive roles of common shocks and diffusion.

Closed-Economy Comparative-Political-Economy (C-CPE):

In closed-polity CP and closed-polity-and-economy CP, domestic political and economic institutions (*e.g.*, electoral systems and central-bank autonomy), structures (*e.g.*, socioeconomic-cleavage and economic-industrial structures), and conditions (*e.g.*, electoral competitiveness and business cycles) are the paramount explanitors of domestic outcomes. Such domestic-primacy substantive stances imply theoretical and empirical models of this

[3] One could substitute comparative and international politics for comparative and international political economy without any loss of applicability in all of the following discussion. The issues discussed are perhaps more homogenous and clearer in the political-economy subfields, though, so we conduct the discussion in those terms.

form:

$$\mathbf{y}_{it} = \xi_{it}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_{it} \tag{A}$$

where $\boldsymbol{y}_{it}$ are the policies or outcomes to be explained (dependent variables) and ξ_{it} are the *domestic* institutional, structural, and other conditions that explain them (independent variables), each of which may vary across time and/or space. Most early 'quantitative' empirical studies in comparative politics and political economy were of this form,[4] perhaps allowing the stochastic component, $\boldsymbol{\varepsilon}_{it}$, to exhibit some spatial correlation, but treating this correlation as nuisance either to be 'corrected' by Parks procedure (FGLS) or, later, to require an adjustment to standard-errors (PCSE). Examples here include most of the early empirical literature on the political economy of fiscal and monetary policy (*e.g.*, Tufte 1978, Hibbs 1987, and successors), coordinated wage bargaining and corporatism (*e.g.*, Cameron 1984, Lange 1984, Lange and Garrett 1985, and successors), and the early central-bank-independence literature (*e.g.*, Cukierman 1992, Alesina and Summers 1993, and successors).

Orthogonal Open-Economy Comparative-Political-Economy (O-O-CPE):

As economies grew more open and interconnected by international trade and, later, finance, through the postwar period, and as perhaps their geopolitical interconnectedness increased also, comparativists and comparative political-economists began to consider controlling for the effects of global political and economic conditions on domestic policies and outcomes to be more important. At first, however, such global conditions were assumed to impact all domestic units equally and to induce equal responses from each domestic unit to that impact. This implies theoretical/empirical models of the following form:

$$\mathbf{y}_{it} = \xi_{it}\boldsymbol{\beta}_0 + \eta_t\boldsymbol{\beta}_1 + \boldsymbol{\varepsilon}_{it} \tag{B}$$

where the η_t are global shocks (e.g., the oil crises), felt equally by all of the sample spatial units (each feels an identical η_t), each of whom respond equally (by amount $\boldsymbol{\beta}_1$) thereto. Again, the stochastic component, $\boldsymbol{\varepsilon}_{it}$, may exhibit spatial correlation—i.e., spatial correlation

[4] Many early 'qualitative' studies also tended to ignore the spatial interdependence of their subject(s), or, at most, to mention the international context as among explanatory factors but generally elaborating little. Moreover, many modern political-economy studies, of both 'quantitative' and 'qualitative' varieties continue to ignore the spatial interdependence of their data (see Persson and Tabellini 2004, e.g.).

distinct from that induced by exposure to these common shocks—but any such correlation was treated as nuisance either to be 'corrected' by Parks procedure (FGLS) or, later, to require an adjustment to standard-errors (PCSE). Examples of empirical models reflecting such stances (often implicit) include many post-oil-crisis political-economy studies, including later rounds of the above literatures wherein time-period dummies or controls for global economic conditions began to appear: e.g., Alvarez, Garrett, and Lange (1991) with regard to partisanship and corporatism interactions; Alesina, Roubini, and Cohen (1997) with regard to political and/or partisan cycles; Powell and Whitten (1993) with regard to economic voting.

Context-Conditional Open-Economy Comparative-Political-Economy (CC-O-CPE):

Modern approaches to CP and CPE recognize the potentially large effects of global shocks and other conditions abroad on the domestic political economy, tending to emphasize how domestic institutions, structure, and conditions shape the degree and nature of domestic exposure to such shocks/conditions and moderate the domestic policy and outcome responses to these differently felt foreign stimuli. This produces characteristic theoretical and empirical models of the following sort:

$$\mathbf{y}_{it} = \xi_{it}\boldsymbol{\beta}_0 + \eta_t\boldsymbol{\beta}_1 + \left(\xi_{it} \cdot \eta_t\right)\boldsymbol{\beta}_3 + \boldsymbol{\varepsilon}_{it} \qquad \text{(C)}$$

where the incidence, impact, and/or effects of global shocks, η_t, on domestic policies and outcomes, $\boldsymbol{y}_{it}$, are conditioned by domestic institutional-structural-contextual factors, ξ_{it}, and so differ across spatial units. Examples here include much of modern CP and CPE, including all of the contributions to the recent *International Organization* special issue (Bernhard, Broz, and Clark 2002), on the choice of exchange-rate regimes (an international, or, at least, foreign-policy, institution) and other monetary institutions. Once more, any spatial correlation distinct from that induced by common or correlated responses to globally *common shocks* would be left to FGLS or PCSE "corrections".[5]

[5] Such arguments that varying domestic institutions and structure condition the response of policies and outcomes to globally common shocks are also central to Franzese (2002). However, the estimated empirical models in that book are of type D, even though the resulting IPE and diffusion aspects receive little emphasis.

International Political-Economy (with Diffusion):

$$\mathbf{y}_{it} = \rho \sum_{j \neq i} w_{ij} \mathbf{y}_{j,t} + \xi_{it} \boldsymbol{\beta}_0 + \eta_t \boldsymbol{\beta}_1 + (\xi_{it} \cdot \eta_t) \boldsymbol{\beta}_3 + \boldsymbol{\varepsilon}_{it} \tag{D}$$

where $\mathbf{y}_{j,t}$, the outcomes in the other ($j \neq i$) spatial units in some manner (given by ρw_{ij}) directly affect the outcome in spatial unit i. Note for future reference that w_{ij} reflects the degree of connection from j to i, and ρ reflects the impact of the outcomes in the other ($j \neq i$) spatial units, as weighted by w_{ij}, on the outcome in i. The rest of the right-hand-side model reflects the domestic political economy and, in the literature, has been as simple as (A) or as complex as (C). Examples of these sorts of models include the recent work of Simmons and Elkins (2004) on the global diffusion of liberalization policies and reforms.[6] Franzese (2003) also estimates such a model in a context where domestic inflation policy/outcomes depend upon inflation rates in other countries, weighted (w_{ij}) in a manner determined by patterns of international monetary exposure and exchange-rate commitments.

Given that models of sort (D) subsume those of sorts (A)-(C), one might argue that scholars should perhaps always begin with (D) and work downward as their data suggest/allow. However, as we elaborate below, obtaining "good" (unbiased, consistent, efficient) estimates of models of type (D) and distinguishing open-economy CPE processes from IPE processes, which entail diffusion, are both less straightforward than they may first appear.

Estimating Spatial Lag Models

The spatial lag model can be used to test hypotheses about and estimate the strength of international diffusion. The model is written formally as

$$\mathbf{y} = \rho \mathbf{W} \mathbf{y} + \mathbf{X} \boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{1}$$

where $\mathbf{y}$ is a NTx1 vector of observation on the dependent variable stacked by unit, ρ is the spatial autoregressive coefficient, $\mathbf{W}$ is an NTxNT block diagonal spatial weighting matrix, $\mathbf{Wy}$ is the spatial lag, $\mathbf{X}$ is a stacked NTxK matrix of values on K independent variables, $\boldsymbol{\beta}$ is a Kx1 vector of coefficients, and $\boldsymbol{\varepsilon}$ is a NTx1 vector or disturbances. Each TxT block

[6] Franzese (2002) also estimates simple, unweighted (*i.e.*, constant w_{ij}) versions of models of type (D), but the discussion there emphasizes the context-conditional CPE aspects of such models.

along $\mathbf{W}$'s diagonal is a matrix of zeros (unless disturbances also correlate temporally, in which case only the prime diagonal is zero and the off-diagonals of these TxT blocks on the diagonal are non-zero and reflect these temporal correlations); each of the off-diagonal TxT blocks has zero off-diagonal elements (unless disturbances also correlate spatially-and-cross-temporally) but non-zero diagonal elements (reflecting the contemporaneous spatial correlation).[7] Recall that the w_{ij} elements of $\mathbf{W}$ reflect the degree of connection from unit j to i—so, for one thing, $\mathbf{W}$ need not be symmetric—and ρ reflects the impact of the outcomes in the other ($j \neq i$) spatial units, as weighted by w_{ij}, on the outcome in i.

Several ways to estimate this model's coefficients exist. One could estimate $\boldsymbol{\beta}$ by ordinary least-squares (OLS) a regression that ignores the spatial interdependence. We refer to this method as non-spatial OLS. This strategy is the simplest, but its estimates will almost certainly suffer from omitted variable bias and/or inefficiency. A second strategy, also simple to implement, is to estimate ρ and $\boldsymbol{\beta}$ by OLS estimation of a model that includes both $\mathbf{Wy}$ and $\mathbf{X}$ on the right-hand side. We refer to this as spatial OLS or, following Land and Deane (1991), as the generalized population potentials estimator (GPP). Unfortunately, because $\mathbf{Wy}$ is endogenous (as explained below), GPP estimates suffer from a simultaneity bias. The two simple estimators, OLS and GPP, are inconsistent; i.e., their estimates of model parameters do not converge to the true parameter values as the sample size increases. A third estimate strategy is to estimate ρ and $\boldsymbol{\beta}$ by maximum likelihood in a model that specifies the endogeneity of $\mathbf{Wy}$ (Ord 1975). This MLE approach can be very difficult to implement in models with any but the simplest forms of spatial dependence, but its parameter estimates would be consistent and efficient.[8] A fourth strategy is to instrument for $\mathbf{Wy}$ using $\mathbf{X}$ and $\mathbf{WX}$. This approach, which we label "spatial two-stage least squares" (S2SLS), would produce consistent and asymptotically efficient, like all appropriately

[7] Much of the methodological literature on spatial dependence focuses on cross-sections of data (T = 1). For a comprehensive treatment of spatial econometrics, see Anselin 1988, and for new developments, see Anselin 2001.
[8] More precisely, as with all MLE, such estimates would, if the model is correctly specified, be *BANC*: "best asymptotic-normal and consistent", i.e., most efficient among estimators that are consistent and asymptotically normally distributed.

specified 2SLS-IV estimates do.[9]

Review of Previous Comparisons of Estimation Strategies for Spatially Interdependent Data

A comprehensive review of the literature comparing estimators for the spatial lag model is beyond the scope of this paper but we highlight four studies that are particularly important for our own, beginning with Doreian (1981), which offers one of the earliest empirical comparisons of non-spatial OLS, GPP, and MLE. He evaluates these estimators in a replication of Mitchell's (1969) analysis of the Huk Rebellion and in several analyses of vote shares for Democratic presidential candidates in Louisiana parishes. In these and other early comparisons, MLE, which is known to produce BANC estimates, provides the benchmark-optimal estimates. Doreian finds that the non-spatial OLS coefficient estimates are inflated relative to the GPP and MLE estimates. That is, either the simple GPP or the complex MLE models sufficed to show that non-spatial OLS tends to inflate estimates of non-spatial regressors and to improve those estimates. In our substantive terms, non-spatial OLS tends to find too large effects of domestic conditions on domestic policies and outcomes because it omits the diffusion of conditions abroad, and either the simple spatial-OLS approach or the fuller MLE approach may suffice to improve those non-spatial estimates. However, Doreian's GPP and MLE estimates of the magnitudes of diffusion are similar in the vote-share analyses but not in the Huk-rebellion analyses. That is, although either GPP or MLE seemed sufficient to demonstrate the typical biases of non-spatial OLS and to improve estimates of the effects of non-spatial factors, the simpler GPP will not always give good estimates of diffusion itself or improve estimates of non-spatial effects as well as does MLE.

Doreian, Teuter, and Wang (1984) compare the same three estimators using Monte Carlo experiments. In their simulations with spatially dependent units, Doreian et al. find that non-spatial OLS gives inflated coefficients on average while the OLS standard errors underestimate the true sample variability. Thus, analysts using non-spatial OLS are more likely to make Type I inferential errors than their p-values suggest. That is, they find once

[9] This list of estimators is far from exhaustive. For a more complete one, see Kelejian et al. (2003). See Kelejian and Robinson (1993) for a technical treatment of the spatial two-stage least squares estimator.

again that non-spatial OLS will tend to over-estimate the effects of non-spatial factors when spatial interdependence is in fact present but now also that, additionally, non-spatial OLS standard errors will tend to be too low. Of course, that combination implies greater t-ratios than warranted (for both numerator and denominator reasons), and so over-confident conclusions for over-sized effects for non-spatial factors. However, exploring Doreian's earlier speculation, these Monte Carlo experiments now show that, for $\rho > 0.1$, GPP tends to overestimate ρ and underestimate the other coefficients. Moreover, the GPP standard errors tend to underestimate true sample variability also. Thus, at least where spatial dependence of appreciable average magnitude exists, spatial OLS tends to incur the converse danger of over-confidently over-estimating diffusion effects while underestimating non-spatial effects. We refer to this phenomenon as the inverse spatial Hurwicz bias and the problematic tradeoff it suggests as the spatial Hurwiczian dilemma (see below). Again, the conclusion is that MLE is preferred, although the much simpler GPP may still be acceptable, but now apparently in more-limited scenarios.

Land and Deane (1992) offer one of the earliest evaluations of the two-stage least-squares instrumental-variable approach to estimating models of spatial interdependence. They compare two similar 2SLS estimators[10] with non-spatial OLS and MLE. They find that both 2SLS estimators and the ML estimator produce similar results that, in turn, differ from non-spatial OLS estimates. They conclude once again that the non-spatial OLS estimates are decidedly inferior. Kelejian, Prucha, and Yuzefovich (2003) conduct Monte Carlo experiments that compare the spatial two-stage least-squares estimator (S2SLS) and GPP (among others). They use a first order autoregressive spatial model with first order autoregressive disturbances to generate their experimental data. In such data, they find the S2SLS estimator generally outperforms GPP by the root mean squared error (RMSE) criterion, although not too notably so under when ρ is small.

Design of Our Monte Carlo Experiments

We use a reduced form of the spatial-lag model to generate the data for our

[10] The only difference is whether one instruments for **WY** at the first stage or for **Y** only in the first stage, applying **W** to the instrumented **Y** in the next step.

experiments:[11]

$$\mathbf{y} = (\mathbf{I} - \rho\mathbf{W})^{-1}\mathbf{X}\beta + (\mathbf{I} - \rho\mathbf{W})^{-1}\varepsilon \tag{2}$$

Our $\mathbf{X}$ matrix (of non-diffusion elements) has three parts: $\boldsymbol{\xi}$, $\boldsymbol{\eta}$, and $\boldsymbol{\xi\eta}$. The vector $\boldsymbol{\xi}$ is an NTx1 stack of *i.i.d.* draws from a standard normal distribution. These observations, unique to each spatial unit in each time period, represent purely domestic variables. Analytically, these $\boldsymbol{\xi}$ represent the set of domestic institutions, structures, and conditions that exist in each unit *i* at each time *t*. The vector $\boldsymbol{\eta}$ is an NTx1 stack of T vectors, each Nx1 in size, and each element of which is identical. That is, each of the T vectors has N elements that are all the same, but each of the T vectors can differ from the others. Thus, $\boldsymbol{\eta}$ represents a set of globally common shocks, one occurring in each of the T periods. These shocks are also drawn *i.i.d.* from a standard normal distribution. The interaction term, $\boldsymbol{\xi\eta}$, captures the idea that the effects of common external shocks are mediated by domestic variables. In other words, our domestic model is of the context-conditional-open-CPE sort. Additionally, however, the model will involve diffusion of the sort IPE implies, with average magnitude ρ and with specific connections from unit *j* to unit *i* of magnitudes w_{ij}.

Drawing the data for $\boldsymbol{\xi}$, $\boldsymbol{\eta}$, and $\boldsymbol{\xi\eta}$—i.e., for $\mathbf{X}$—in this manner, we then generate the data for **Y** using two different sets of coefficients, $(\beta_1, \beta_2, \beta_3, \rho)$, and three different spatial weighting matrices, **W**, in (2). For coefficients, we use $(\beta_1, \beta_2, \beta_3, \rho) = (1,1,1,0.1)$ and $(\beta_1, \beta_2, \beta_3, \rho) = (1,1,1,0.5)$. Note that one set of coefficients has smaller ρ than the other, and recall that the spatial weighting matrix determines the relative importance of each unit to each of the others in the pattern of spatial diffusion while ρ determines the average strength of diffusion. Thus, the second set of coefficients represents a stronger diffusion process. We assume the spatial weights are time-invariant so all the elements along the diagonals of the TxT off-diagonal blocks of $\mathbf{W}$ are the same. That is, only one w_{ij} connecting *j* to *i* persists for all T periods; this connectivity does not change from period to period. We use three rules to generate the patterns of interdependence between spatial units. We first set all of these w_{ij} equal to 1/(N-1). In this case, every unit affects every other unit equally, and the appropriate

[11] Our model differs from Kelejian et al.'s in that we use spatially orthogonal disturbances.

right-hand-side variable for each unit-year to reflect this proposition would be an unweighted average of the dependent variable for the other units in that year. For the second spatial weighting matrix we add a random draw from a uniform distribution with support [–0.1, +0.1] to 1/(N-1). This represents a pattern of diffusion that differs from the all-equal one just described by a relatively small amount. For the third matrix we added a random draw from a uniform distribution with support [–0.5, +0.5], representing a pattern of diffusion that differs from the all-equal one by a greater amount. We generate samples with dimensions N = 5, 20, 30, 40, 50 and T = 20, 30, 40, 80.

We evaluate the non-spatial OLS, GPP (spatial OLS), and spatial 2SLS estimators. To use GPP or S2SLS, a spatial weighting matrix must be specified. For estimation, we set all non-zero elements of $\mathbf{W}$ to 1/(N-1). That is, the hypothetical researcher estimates an equation with a spatial lag given by the unweighted average of the dependent variable in the other cross-sectional units each period on the right-hand-side, with or without instrumentation in the S2SLS or GPP cases, respectively. Thus, in the first group of experiments—the all-equal diffusion case—the weighting matrix used for estimation will be the true weighting matrix. In the others, the weighting matrix will contain imperfect but unbiased estimates of the true spatial weights, the degree of imperfection greater in the case where the true weights vary uniformly about equal weights plus or minus 0.5. This imperfection reflects the realism that $\mathbf{W}$ is not observed, so analysts will rarely use the true spatial weighting matrix, but rather some theoretically or conveniently specified approximation to it (guess at it), for estimation. Our addition of the second and third spatial-weighting matrices allows us to explore the consequences of analysts using the wrong $\mathbf{W}$. As noted, our spatial lag for the GPP estimator amounts to putting the average-y from the other N-1 units on the right-hand side of the regression model as, for example, Franzese (2002) does. The results for each of our Monte Carlo experiments are based on 100 simulations. We report the mean, minimum, and maximum coefficient and standard error estimates as well as their standard deviation.

Simulation Results

We discuss a subset of the results from the Monte Carlo experiments—N=5,40;

$T=20,40$; $\rho=0.1,0.5$; $w_{ij}=1/(N-1)$, $(1/(N-1))+U[-0.1,+0.1]$. The full set is reported in the appendix. We start by comparing the two simple but inconsistent estimators: OLS and GPP. Is it ever reasonable to use these estimators? How large are their respective biases? Table 1 gives the results for $\rho=0.1$ and $w_{ij}=1/(N-1)$. In these experiments, the spatial weights are correctly specified and the diffusion is relatively weak. Therefore, we expect the omitted-variable and simultaneity biases to be small such that OLS performs somewhat but not terribly poorly and GPP offers some improvement over that. Intuitively, the omitted variable bias in the OLS estimates manifests primarily in β_2, the coefficient on the common shock. On average, OLS overestimates the (so-called) direct effect of these common shocks. The bias ranges in size from 0.109 to 0.133 (i.e., about 12%—recall that the true parameter values are 1). All of the other parameter estimates are very close to their true values. The average GPP estimates of β_2 are indeed much better. The size of the biases ranges from –0.021 to +0.029 (or about 2.5%). GPP underestimates β_2 in three of the experiments and overestimates the coefficient in one. The biases in the GPP estimates of β_2 and ρ also seem to be negatively related, which is likewise intuitive. When β_2 (the effect of common shocks) is overestimated/underestimated ρ (the strength of diffusion) is underestimated/overestimated. This robust finding—which suggests it may be difficult to isolate the effects of common external shocks from diffusion using the OLS and GPP estimators—is consistent with the results of the Doreian et al. (1984) study.

Table 1. Comparing Estimators (ρ = 0.1, w_{ij} = 1/(N-1))

		OLS				GPP			
		Mean	Stdev	Min	Max	Mean	Stdev	Min	Max
	β_1	1.006	0.113	0.76	1.299	0.998	0.111	0.766	1.281
	s.e.(β_1)	0.105	0.011	0.084	0.134	0.105	0.011	0.084	0.133
N=5	β_2	1.114	0.107	0.851	1.391	0.994	0.183	0.573	1.778
T=20	s.e.(β_2)	0.104	0.018	0.067	0.15	0.163	0.032	0.111	0.268
	β_3	1.002	0.118	0.721	1.297	0.999	0.117	0.721	1.316
	s.e.(β_3)	0.109	0.023	0.068	0.185	0.11	0.023	0.069	0.187
	ρ					0.11	0.137	-0.467	0.428
	s.e.(ρ)					0.113	0.021	0.074	0.182
	β_1	1.009	0.075	0.813	1.203	1.003	0.074	0.811	1.195
	s.e.(β_1)	0.073	0.006	0.059	0.086	0.073	0.006	0.059	0.086
N=5	β_2	1.133	0.078	0.905	1.345	0.991	0.111	0.743	1.307
T=40	s.e.(β_2)	0.071	0.009	0.054	0.102	0.115	0.014	0.087	0.151
	β_3	1.007	0.062	0.862	1.19	1.005	0.064	0.853	1.186
	s.e.(β_3)	0.074	0.01	0.053	0.104	0.074	0.01	0.053	0.104
	ρ					0.123	0.08	-0.128	0.297
	s.e.(ρ)					0.077	0.009	0.057	0.104
	β_1	1.005	0.038	0.87	1.077	1.004	0.038	0.867	1.078
	s.e.(β_1)	0.036	0.002	0.032	0.045	0.036	0.002	0.032	0.045
N=40	β_2	1.109	0.049	0.911	1.207	1.029	0.215	0.629	1.788
T=20	s.e.(β_2)	0.036	0.006	0.026	0.054	0.147	0.034	0.094	0.25
	β_3	0.996	0.036	0.882	1.083	0.996	0.036	0.881	1.08
	s.e.(β_3)	0.037	0.006	0.027	0.059	0.037	0.006	0.026	0.059
	ρ					0.073	0.182	-0.622	0.413
	s.e.(ρ)					0.128	0.03	0.074	0.208
	β_1	1.001	0.024	0.917	1.06	1	0.024	0.915	1.06
	s.e.(β_1)	0.025	0.001	0.024	0.029	0.025	0.001	0.024	0.029
N=40	β_2	1.115	0.027	1.054	1.173	0.979	0.105	0.731	1.278
T=40	s.e.(β_2)	0.025	0.003	0.019	0.033	0.097	0.014	0.052	0.139
	β_3	1.002	0.022	0.94	1.069	1.002	0.022	0.944	1.064
	s.e.(β_3)	0.026	0.003	0.019	0.034	0.026	0.003	0.019	0.034
	ρ					0.121	0.089	-0.105	0.334
	s.e.(ρ)					0.084	0.012	0.047	0.116

When T is small (relative to N) the mean reported standard errors seem to underestimate the true variability in the GPP estimator.[12] This is particularly true for the standard errors on β_2 and ρ. When N=40 and T=20 the mean reported standard error for β_2 underestimates the standard deviation of the coefficient estimates by 32% (0.147 vs. 0.215).

[12] This is also consistent with Doreian et al. (1984). Panel-corrected standard-errors (PCSEs) may provide better estimates (Beck and Katz 1995), but we have not explored this yet.

The mean reported standard error for ρ underestimates the true sampling variability by 30% (0.128 vs. 0.182). These numbers drop to 8% and 6% respectively when T is increased to 40, but the problem worsens as N increases. When N=5 and T=20 the mean reported standard errors for β_2 and ρ underestimate the observed sample variability by 11% and 18% respectively. Thus, samples with larger time dimensions relative to cross-sectional ones seem to aid separating common shocks from diffusion and obtaining accurate estimates of the standard errors of these distinct effects.

Table 2 reports the results for ρ=0.1 and w_{ij}=1/(N-1)+U[-0.1,+0.1]. Note that the true proportionate variation in the relative strength of cross-unit connections is quite sizable in this example. With N=5, 1/(N-1)=.25, so plus or minus .1 is plus or minus 40%. With N=40, 1/(N-1)≈.025, so plus or minus .1 is plus or minus roughly 400%. Still, given that the true spatial weights are randomly distributed about those used by the analyst in the estimation, we might expect little change in the bias properties of either non-spatial OLS or GPP while the sampling variability for both estimators should increase. Furthermore, since the GPP estimator uses an imperfect (although unbiased) spatial weighting matrix, we might expect these estimates to offer a lesser improvement over non-spatial OLS than it did in the example of Table 1 where the estimator used exactly the right weighting matrix. The overall (average) strength of diffusion remains weak in this example, though, so these differences from Table 1 should not be too great. Interestingly, the OLS estimates exhibit no glaring differences from those reported in Table 1. As for the GPP estimates, when N is small, they are slightly worse (in terms of bias) than the corresponding estimates in Table 1, although still yielding a notable improvement over the non-spatial OLS estimates. The largest differences again concentrate in the estimates for β_2, and over-/underestimation of ρ again seems associated with under-/overestimation of β_2. However, a systematic increase in the sampling variability of the GPP estimator actually fails to materialize, although the mean reported standard errors continue to underestimate the true variability in the estimator when T is small.

Table 2. Comparing Estimators (ρ = 0.1, w_{ij} = 1/(N-1) + U[-0.1,+0.1])

		OLS				GPP			
		Mean	Stdev	Min	Max	Mean	Stdev	Min	Max
	β_1	0.996	0.113	0.685	1.315	0.99	0.114	0.685	1.359
	s.e.(β_1)	0.106	0.013	0.082	0.14	0.106	0.013	0.082	0.141
N=5	β_2	1.121	0.109	0.856	1.418	1.021	0.196	0.547	1.606
T=20	s.e.(β_2)	0.103	0.017	0.064	0.152	0.168	0.032	0.1	0.258
	β_3	1.009	0.128	0.64	1.36	1.001	0.129	0.613	1.316
	s.e.(β_3)	0.108	0.023	0.061	0.196	0.109	0.024	0.062	0.202
	ρ					0.085	0.152	-0.263	0.48
	s.e.(ρ)					0.116	0.022	0.067	0.18
	β_1	1.011	0.073	0.848	1.21	1.006	0.071	0.838	1.185
	s.e.(β_1)	0.073	0.005	0.059	0.091	0.072	0.005	0.059	0.092
N=5	β_2	1.108	0.077	0.905	1.307	0.959	0.129	0.692	1.337
T=40	s.e.(β_2)	0.072	0.009	0.058	0.101	0.112	0.016	0.085	0.16
	β_3	1.005	0.069	0.811	1.194	1.006	0.071	0.82	1.211
	s.e.(β_3)	0.074	0.01	0.056	0.102	0.074	0.01	0.054	0.102
	ρ					0.135	0.093	-0.102	0.36
	s.e.(ρ)					0.077	0.01	0.058	0.108
	β_1	1.003	0.033	0.924	1.072	1.003	0.033	0.925	1.073
	s.e.(β_1)	0.037	0.002	0.033	0.042	0.037	0.002	0.033	0.042
N=40	β_2	1.113	0.042	1.038	1.255	1.011	0.194	0.709	1.707
T=20	s.e.(β_2)	0.038	0.007	0.024	0.068	0.147	0.03	0.083	0.249
	β_3	0.998	0.04	0.888	1.082	0.997	0.041	0.887	1.081
	s.e.(β_3)	0.039	0.007	0.025	0.068	0.039	0.007	0.025	0.067
	ρ					0.089	0.17	-0.575	0.365
	s.e.(ρ)					0.128	0.026	0.072	0.222
	β_1	0.999	0.025	0.939	1.05	0.999	0.025	0.937	1.054
	s.e.(β_1)	0.025	0.001	0.023	0.028	0.025	0.001	0.023	0.028
N=40	β_2	1.109	0.028	1.046	1.179	0.985	0.11	0.756	1.29
T=40	s.e.(β_2)	0.025	0.003	0.019	0.032	0.098	0.014	0.063	0.138
	β_3	0.998	0.027	0.933	1.068	0.998	0.027	0.933	1.07
	s.e.(β_3)	0.026	0.003	0.021	0.033	0.026	0.003	0.021	0.033
	ρ					0.112	0.1	-0.18	0.34
	s.e.(ρ)					0.085	0.012	0.056	0.119

In sum, when the overall strength of diffusion is relatively low (0.1 in these examples), non-spatial OLS tends to over-estimate the effects of common shocks appreciably, and does so overconfidently, more or less independently of the degree of variation in the strengths of cross-unit connections. Meanwhile, at least when the overall strength of diffusion remains relatively low, Spatial OLS (GPP) offers a marked reduction in this bias, although it too tends to underestimate standard errors. Neither the degree of improvement offered by spatial over non-spatial OLS nor the overconfidence of the spatial

OLS estimator seems to depend in any simple, monotonic way on the degree of variation in the relative strength of specific cross-unit connections. Rather, the degree to which spatial OLS mis-estimates the overall strength of diffusion, with the concurrent mis-estimation in the other direction of the effect of common shocks, seems to become more dependent upon and vary more with the NxT sample dimensions as cross-unit connections become more heterogenous and less-well modeled by the analyst. I.e., the reductions in bias and overconfidence offered by spatial over non-spatial OLS seems more variant across sample dimensions in Table 2 than in Table 1. Thus, while spatial OLS clearly improves upon non-spatial OLS in estimating the effects of common shocks, at least for relatively low overall strengths of diffusion, it also tends still to mis-estimate the overall strength of diffusion, by between about 10% and 30% in these examples, with a commensurate mis-estimation in the opposite direction of common-shock effects.

Table 3 gives the results for a greater overall strength of diffusion, ρ=0.5, and w_{ij}=1/(N-1). With stronger diffusion, we expect the omitted-variable and simultaneity biases to be larger, and a severe positive omitted-variable bias does indeed manifest in all four non-spatial OLS estimates. The bias is approximately +1.00 (or +100%) for all four sample-dimensions. The estimates for β_1 and β_3 are also inflated, although the size of these biases shrinks as N grows. For N=5 and T=20, the biases are +0.12 and +0.098 respectively. These biases drop to +0.017 and +0.005 when N=40. Moreover, the mean reported standard errors once again underestimate the estimator's true sampling variability, for all three coefficients, especially when N and T are small. For N=5 and T=20, the mean reported standard errors underestimate the standard deviation of the coefficient estimates for β_1, β_2, and β_3 by 15%, 48%, and 23%. When N is increased to 40, the mean standard errors underestimate the observed sampling variability by 7%, 66%, and 0%. Once again, the problems tend to concentrate in the estimates, coefficients and standard errors, of the unmoderated common-shock effect. When N and T are 40, however, non-spatial OLS does not underestimate the sampling variability for β_1 or β_2, but it does for β_3 (by 60%).[13] We do not yet have an intuition for this result, except to note that this is the one case where the sample's N and T

[13] These results support Doreian et al.'s conclusion that non-spatial OLS produces inflated coefficient estimates and compressed standard errors.

dimensions are equal. Across the board, though, the average GPP (spatial OLS) estimates, while not perfect, are far better than the non-spatial OLS estimates. Again, biases in the GPP estimates of β_2 and ρ seem to be negatively related; in this case, GPP overestimates ρ and underestimates β_2, each by between about 14% and 18%, depending on the sample dimensions. Intuitively, the endogenous spatial-lag 'steals explanatory power' from the common shocks variable, much like the tendency for temporal lags to 'steal explanatory power' from trended variables (Achen 2000). In sum, as the general strength of diffusion increases, non-spatial OLS seems to perform increasingly poorly in terms of both the bias and the overconfidence of its estimates of non-spatial factors' effects, most especially regarding the size and standard errors of common-shock effects. Spatial OLS continues to offer considerable improvements in terms of reducing these biases as the general strength of diffusion increases, but its tendency to overestimate the strength of diffusion and underestimate the impact of common shocks also continues, as does its tendency to underestimate sampling variability, a flaw both OLS estimators share.

Table 3. Comparing Estimators (ρ = 0.5, w_{ij} = 1/(N-1))

		OLS				GPP			
		Mean	Stdev	Min	Max	Mean	Stdev	Min	Max
	β_1	1.122	0.165	0.792	1.557	0.981	0.109	0.739	1.266
	s.e.(β_1)	0.14	0.018	0.105	0.201	0.105	0.011	0.085	0.133
N=5	β_2	1.994	0.263	1.136	2.431	0.83	0.158	0.439	1.314
T=20	s.e.(β_2)	0.138	0.024	0.081	0.203	0.171	0.035	0.113	0.31
	β_3	1.098	0.19	0.652	1.661	0.986	0.114	0.727	1.284
	s.e.(β_3)	0.146	0.031	0.083	0.224	0.109	0.023	0.068	0.184
	ρ					0.588	0.069	0.375	0.744
	s.e.(ρ)					0.068	0.014	0.044	0.121
	β_1	1.123	0.111	0.811	1.397	0.984	0.073	0.803	1.157
	s.e.(β_1)	0.098	0.009	0.079	0.121	0.073	0.006	0.06	0.087
N=5	β_2	2.062	0.188	1.613	2.547	0.831	0.105	0.573	1.12
T=40	s.e.(β_2)	0.096	0.012	0.072	0.126	0.119	0.015	0.09	0.154
	β_3	1.104	0.102	0.888	1.404	0.989	0.065	0.847	1.151
	s.e.(β_3)	0.099	0.013	0.072	0.132	0.074	0.01	0.053	0.104
	ρ					0.59	0.045	0.459	0.673
	s.e.(ρ)					0.046	0.006	0.034	0.065
	β_1	1.017	0.041	0.873	1.114	1.003	0.037	0.871	1.076
	s.e.(β_1)	0.038	0.002	0.032	0.048	0.036	0.002	0.032	0.045
N=40	β_2	1.997	0.111	1.614	2.223	0.855	0.165	0.538	1.437
T=20	s.e.(β_2)	0.038	0.006	0.027	0.057	0.148	0.035	0.095	0.255
	β_3	1.005	0.039	0.892	1.101	0.995	0.036	0.879	1.076
	s.e.(β_3)	0.039	0.006	0.027	0.06	0.037	0.006	0.026	0.059
	ρ					0.572	0.078	0.285	0.728
	s.e.(ρ)					0.072	0.017	0.041	0.118
	β_1	1.014	0.026	0.943	1.077	0.998	0.024	0.913	1.06
	s.e.(β_1)	0.027	0.001	0.025	0.03	0.025	0.001	0.024	0.029
N=40	β_2	2.011	0.067	1.864	2.155	0.832	0.099	0.537	1.091
T=40	s.e.(β_2)	0.027	0.003	0.02	0.034	0.098	0.014	0.052	0.14
	β_3	1.014	0.027	0.939	1.1	1	0.022	0.943	1.059
	s.e.(β_3)	0.027	0.003	0.02	0.035	0.026	0.003	0.019	0.034
	ρ					0.585	0.047	0.447	0.723
	s.e.(ρ)					0.047	0.007	0.026	0.065

Table 3 represented the case of strong, all-equal diffusion perfectly modeled by the analyst. Table 4 reports the results for ρ=0.5 and w_{ij}=1/(N-1)+U[-0.1,+0.1]; i.e., the case of strong diffusion with cross-unit connections varying from dyad to dyad and this variation being imperfectly modeled by the analyst. Unlike the analogous cases in Table 2 of varying, imperfectly modeled cross-unit connections but weak general diffusion compared with Table 1 of all-equal and weak diffusion, the sampling variability of the estimators in Table 4 (strong, varying, imperfectly modeled) compared with Table 3 (strong, all-equal, perfectly modeled) does increase. This is especially true for the non-spatial OLS estimate of β_2 when N and T are large. For N=40 and T=40, the change from a fixed to random spatial weighting matrix results in a near 100% increase in the sampling distribution for β_2 (0.067 vs. 0.132). However, this large increase in true variability is not reflected in the standard error estimates, which increase only slightly from 0.027 to 0.029. In other words, the over-confidence of non-spatial OLS increases dramatically from the strong, all-equal, perfectly modeled case to the strong, varying, imperfectly modeled case. For the GPP (spatial OLS) estimator, this problem is most notable for ρ. Not surprisingly GPP continues to overestimate ρ and underestimate β_2. We refer to this latter tendency, now shown to ubiquitous, as spatial (inverse) Hurwicz bias.[14] Notice the tradeoff it establishes between non-spatial OLS, which overestimates common-shock effects and underestimates diffusion (assumes zero, actually) and spatial OLS, which does the reverse. We refer to this tradeoff as a(n) (inverse) Hurwiczian dilemma.

For this set of experiments, we also evaluate the performance of the spatial two-stage least squares estimator, which may offer a way out of the dilemma. Like Kelejian et al. (2003), we find that the S2SLS coefficient estimates to outperform GPP's in terms of bias. Moreover, the estimated standard errors are reasonably accurate. The most significant difference between GPP and S2SLS lies in the estimates of β_2 and ρ. Because of the spatial lag's endogeneity, GPP inflates the importance of diffusion at the expense of common external shocks. The S2SLS estimator does a much better job of distinguishing between the two kinds of effects. For N=5 and T=40, the mean GPP estimate of β_2 is biased by -0.169 whereas the S2SLS bias is -0.008. For this experiment, the average GPP estimate of ρ is off by +0.09 while the bias of the S2SLS estimate is -0.003.

[14] Hurwicz bias is the tendency for OLS estimates of coefficients on temporal lags in pooled time-series-cross-section samples to be underestimated in the presence of cross-sectional fixed effects. This is a small sample bias that vanishes as T increases. Inversely here, OLS with the rough equivalent of time-period fixed effects ($\boldsymbol{\eta}$) tends to overestimate the coefficient on the spatial lag (and underestimate the coefficient on $\boldsymbol{\eta}$).

Table 4. Comparing Estimators ($\rho = 0.5$, $w_{ij} = 1/(N-1) + U[-0.1,+0.1]$)

		OLS				GPP				S2SLS			
		Mean	Stdev	Min	Max	Mean	Stdev	Min	Max	Mean	Stdev	Min	Max
	β_1	1.103	0.167	0.616	1.417	0.977	0.113	0.668	1.366	0.986	0.113	0.677	1.292
	s.e.(β_1)	0.141	0.023	0.105	0.203	0.108	0.013	0.083	0.145	0.11	0.014	0.086	0.145
N=5	β_2	2.04	0.281	1.479	2.688	0.853	0.179	0.328	1.356	1.021	0.249	0.508	1.899
T=20	s.e.(β_2)	0.137	0.026	0.081	0.21	0.179	0.036	0.102	0.285	0.219	0.072	0.106	0.569
	β_3	1.129	0.216	0.611	1.919	0.99	0.13	0.66	1.276	0.999	0.129	0.64	1.327
	s.e.(β_3)	0.144	0.033	0.085	0.24	0.11	0.025	0.062	0.204	0.113	0.026	0.065	0.214
	ρ					0.575	0.084	0.324	0.807	0.493	0.117	0.08	0.698
	s.e.(ρ)					0.07	0.015	0.04	0.112	0.093	0.034	0.044	0.228
	β_1	1.114	0.102	0.923	1.381	0.987	0.07	0.794	1.148	1.004	0.072	0.816	1.175
	s.e.(β_1)	0.098	0.009	0.078	0.124	0.073	0.006	0.059	0.092	0.074	0.006	0.06	0.094
N=5	β_2	1.976	0.214	1.624	2.614	0.808	0.121	0.528	1.108	0.992	0.155	0.588	1.524
T=40	s.e.(β_2)	0.097	0.012	0.076	0.126	0.118	0.017	0.088	0.17	0.141	0.03	0.095	0.256
	β_3	1.085	0.106	0.82	1.41	0.991	0.076	0.829	1.238	1.003	0.075	0.828	1.218
	s.e.(β_3)	0.1	0.013	0.072	0.138	0.075	0.01	0.055	0.102	0.076	0.01	0.056	0.103
	ρ					0.59	0.056	0.454	0.748	0.497	0.069	0.254	0.718
	s.e.(ρ)					0.047	0.007	0.035	0.069	0.061	0.014	0.039	0.106
	β_1	1.017	0.038	0.922	1.109	1.003	0.036	0.922	1.079	1.004	0.036	0.921	1.079
	s.e.(β_1)	0.042	0.003	0.037	0.05	0.041	0.002	0.037	0.049	0.041	0.002	0.037	0.049
N=40	β_2	2.013	0.156	1.702	2.729	0.862	0.164	0.583	1.492	0.974	0.174	0.666	1.688
T=20	s.e.(β_2)	0.043	0.007	0.03	0.073	0.162	0.034	0.094	0.296	0.209	0.067	0.102	0.512
	β_3	1.009	0.049	0.898	1.125	0.995	0.048	0.842	1.109	0.996	0.048	0.842	1.11
	s.e.(β_3)	0.045	0.007	0.031	0.073	0.043	0.007	0.03	0.072	0.043	0.007	0.03	0.072
	ρ					0.569	0.084	0.22	0.727	0.513	0.09	0.197	0.686
	s.e.(ρ)					0.078	0.017	0.045	0.15	0.102	0.034	0.049	0.248
	β_1	1.011	0.027	0.919	1.087	0.996	0.025	0.92	1.066	0.998	0.025	0.92	1.067
	s.e.(β_1)	0.029	0.001	0.027	0.033	0.028	0.001	0.026	0.033	0.028	0.001	0.026	0.033
N=40	β_2	2.011	0.132	1.743	2.354	0.851	0.102	0.637	1.057	1.013	0.127	0.75	1.369
T=40	s.e.(β_2)	0.029	0.003	0.023	0.036	0.108	0.016	0.069	0.152	0.138	0.031	0.073	0.232
	β_3	1.011	0.033	0.932	1.093	0.998	0.032	0.927	1.09	0.999	0.032	0.928	1.09
	s.e.(β_3)	0.03	0.003	0.024	0.037	0.029	0.003	0.024	0.036	0.029	0.003	0.024	0.036
	ρ					0.576	0.06	0.451	0.709	0.495	0.071	0.297	0.657
	s.e.(ρ)					0.052	0.008	0.034	0.074	0.067	0.015	0.036	0.115

Spatial 2SLS instrumental variables (S2SLS-IV) is also relatively easy (relative to MLE, e.g.) to implement. One simply uses the **W** matrix already constructed to generate the spatial lag of **y** to generate the same spatial lags of the **X** variables. These spatially lagged **X** then serve as instruments for the spatial lag of **y**. To elaborate, the endogeneity or simultaneity bias that plagues spatial OLS arises because the spatial lag of **y** on the right-hand side of the model is endogenous to, i.e., simultaneous with, the dependent variable, **y**, on the left-hand side. Thus, a regressor, **Wy**, covaries with the true residual, **ε**, violating one of the classical linear regression model assumptions essential to the unbiasedness and consistency of OLS shown in the Gauss-Markov theorem. The easiest way to recognize this simultaneity intuitively is to note that, whereas units *j* affect unit *i*, which is why we place some weighted average of *j*'s outcomes on the right-hand side in the first place, unit *i* also affects (some) unit(s) *j*, and so the spatial lag **Wy** actually contains some part of *i*'s outcome itself. The standard instrumental-variables "solution" to such endogeneity is to find a (some) variable(s), **Z**, can that covaries (covary) with the endogenous regressor but does (do) not covary with the dependent variable (i.e., **ε**) except insofar as they relate to that regressor. Given such a **Z**, the instrumental-variable estimator, $\mathbf{b_{iv}}=(\mathbf{X'Z})^{-1}\mathbf{Z'Y}$, will be consistent and asymptotically efficient. The two-stage least-squares instrumental-variables (2SLS-IV) produces these properties by, first, regressing the set of **X**, including the endogenous regressor(s), on **Z** and the exogenous regressors, and, second, regressing Y on the fitted **X**'s from this first stage. If the instrument(s) **Z** are indeed perfectly exogenous, i.e., their covariance with **ε**, is *exactly* zero, then these IV estimators will enjoy these properties regardless of how strong the covariance of the instrument(s) with the endogenous regressor(s) for which it (they) instrument(s). If not, i.e, if the instruments are to any degree at all non-zero correlated with **ε**, then the instruments are only *quasi-instruments*, in Bartels (1991) terms, and the mean-squared-error costs or benefits of instrumentation will depend on the ratio of the covariance of the instrument(s) with the endogenous regressor(s) relative to the covariance of the instrument(s) with **ε**. In our experiments, the **X** variables, $\boldsymbol{\xi}$, $\boldsymbol{\eta}$, and $\boldsymbol{\xi\eta}$, are drawn *i.i.d.*, and in particular independent of the draws for **ε**, so our **WX** are perfect instruments by construction. More commonly in practice, however, we expect that researchers will confront right-hand-side **X**-variables that are endogenous to left-hand-side **y**-variables—i.e., the standard endogeneity concern that **y** causes **X** as well as **X** causes **y**. If so, then **WX** will offer imperfect, or *quasi-*, instruments at best (intuitively, because *j*'s **X** will also contain some of *i*'s **y**). In principle, researchers should be able to combine the common 2SLS-IV estimation strategy to address the endogeneity of **X** and **y** with the Spatial 2SLS-IV estimation strategy suggested here to address the spatial simultaneity discussed here. Failing that (e.g., if even imperfectly valid instruments for the common endogeneity problem prove difficult to discover, as they usually do), we expect that the utility of the available **WX**'s as *quasi-instruments* will depend on the relative magnitudes of the intra-$\boldsymbol{\varepsilon}$ diffusion mechanisms, the intra-**X** diffusion mechanisms, call those magnitudes γ and ρ respectively, the causal mechanisms from **y** to **X**, call those magnitudes α, and the causal mechanisms **X** to **y**, call those magnitudes β. However, we have not yet explored this conjecture or described its terms theoretically or in Monte Carlo experimentation, nor have we yet determined the practical details of combining 2SLS-IV for endogeneity of **X** and **y** with Spatial 2SLS-IV for spatial simultaneity of **y**. Therefore, for now, we advise researchers either to employ only strictly exogenous **X** in generating the spatial instruments **WX**, or, if they trust out conjecture, to explain why the **X** used in **WX** have good "Bartels Ratios", which in this case we believe translates to high $\rho\beta/\gamma\alpha$.[15]

Methodological Conclusion

Our experimental results support and extend the existing studies that evaluate estimators for spatial-lag models. We found (a) that non-spatial OLS performs poorly, producing both biased and over-confident estimates, especially of common-shock effects and especially when the degree of spatial diffusion is high, (b) that the GPP estimator (spatial OLS) reduces these biases of non-spatial OLS dramatically, but also tends to under-estimate standard errors and to inflate the spatial lag's coefficient at the expense of other explanatory variables, especially common shocks and especially when the degree of diffusion is high, and (c) that the S2SLS-IV estimator—at least under the ideal conditions for its instrumentation assumptions—improves further upon GPP, producing unbiased estimates of both common shocks and diffusion, and both with reasonable estimates of uncertainty. These

[15] Note: the magnitudes cannot be estimated without a model whose identification conditions must assume them. I.e., as Bartels emphasized, the magnitudes of the parameters that determine the quality of *quasi-instruments* cannot be estimated; we can only offer theoretical arguments about their likely relative magnitudes.

findings generally resonate with those of previous studies where they overlap. Our use of a non-diffusion baseline model that explicitly reflects a modern, context-conditional, open-economy, comparative-political-economy approach, and the finding there that the problems of spatial OLS and, much more so, non-spatial OLS concentrate precisely in this area of distinguishing common-shocks from diffusion is one way in which our results extend previous ones. Another is that previous work studied cross-sections of data almost exclusively, whereas our simulations evaluated non-spatial Spatial OLS (GPP), and S2SLS-IV using panels of data. Varying the sizes of T, of N, and N/T, across our experiments, we found, e.g., that the GPP standard errors improve as T increases.

These results have important implications for the study of political economy. Analysts who ignore diffusion processes when they are present will exaggerate the importance of domestic variables and external shocks (and their interaction). At the same time, analysts who model international diffusion without adequately addressing the inherent simultaneity problems that spatial lags raise will overestimate the importance of diffusion at the expense of common external shocks.

Substantive Empirical Application: International Interdependence in Theoretical and Empirical Models of Capital-Tax Competition

A Stylized Theoretical Model of Capital-Tax Competition

We leverage Persson and Tabellini's (2000: ch. 12) theoretical model to illustrate that tax competition implies spatial interdependence. In brief, the model's essential elements are as follows. In two jurisdictions (countries), denote the domestic and foreign tax rates τ_K and τ_K^*. Individuals can invest capital in either country, but foreign investment incurs *mobility costs*. Taxation follows the source (not the residence) principle. Governments use revenues from taxes levied on capital and labor to fund a fixed amount of spending.[16] Individuals differ in their relative labor to capital endowment, denoted e^i, and make labor-leisure, l and x, and savings-investment, s=k (domestic) + f (foreign), decisions to maximize

[16] The government consumption is not only fixed, but entirely wasted; i.e., it enters no one's utility function.

quasi-linear utility, $\omega=U(c_1)+c_2+V(x)$, over leisure and consumption and in the model's two periods, c_1 and c_2, subject to a time constraint, $1+e^i=l+x$, and budget constraints in each period, $1-e^i=c_1+k+f+\equiv c_1+s$ and $c_2=(1-\tau_k)k+(1-\tau^*_k)f-M(f)+(1-\tau_l)l$.

The equilibrium economic choices of citizens i in this model are as follows:

$$s=S(\tau_k)=1-U_c^{-1}(1-\tau_k)$$

$$f=F(\tau_k,\tau^*_k)=M_f^{-1}(\tau_k-\tau^*_k)$$

$$k=K(\tau_k,\tau^*_k)=S(\tau_k)-F(\tau_k,\tau^*_k)$$

With labor, $L(\tau_l)$, leisure, x, and consumption, c_1, c_2, implicitly given by these conditions, this leaves individuals with indirect utility, W, defined over the policy variables, tax rates, of:

$$W(\tau_l,\tau_k)=U\{1-S(\tau_k)\}+(1-\tau_k)S(\tau_k)+(\tau_k-\tau^*_k)F(\tau_k,\tau^*_k)-M\{F(\tau_k,\tau^*_k)\}+(1-\tau_l)L(\tau_l)+V\{1-L(\tau_l)\}$$

Facing an electorate with these preferences over taxes, using a Besley-Coate (1997) citizen-candidate model wherein running for office is costly and citizens choose whether to enter the race by an expected-utility calculation—some citizen candidate will win and set tax rates to maximize his/her own welfare. The model's stages are: 1) elections occur in both countries, 2) elected citizen-candidates set their respective countries' tax rates, and 3) all private economic decisions are made. In this case, the candidate who enters and wins will be the one with endowment e^P so that s/he desires to implement the following *Modified Ramsey Rule*:

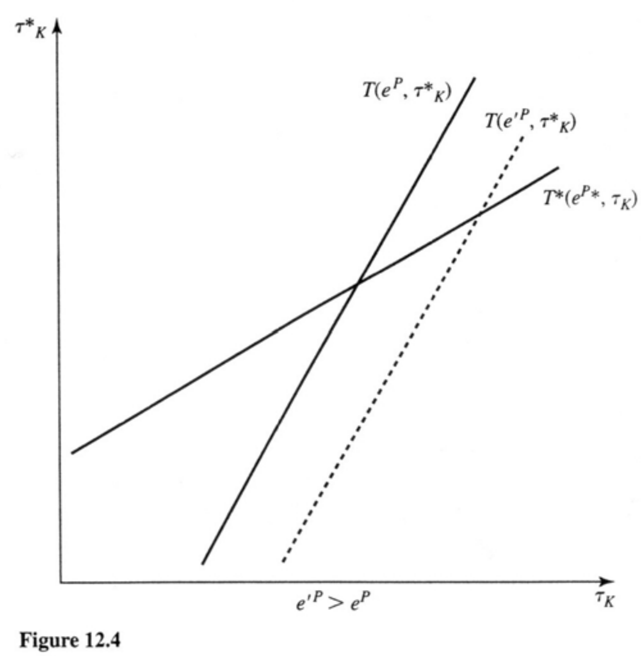
$$\frac{S(\tau_k^p)-e^p}{S(\tau_k^p)}\left[1+\varepsilon_l(\tau_k^p)\right]=\frac{L(\tau_l^p)+e^p}{L(\tau_l^p)}\left[1+\frac{S_\tau(\tau_k^p)+2F_\tau^*(\tau_k^{p*},\tau_k^p)\tau_k}{S_\tau(\tau_k^p)}\right] \quad (3)$$

This would be exactly the Ramsey Rule of optimal taxation, which is to set the elasticities of all tax instruments equal, except for two features of the political-economic setting. First, citizens differ in their capital-labor endowment, median-voter conditions apply, and capital is assumed distributed with right skew. Thus, a standard Meltzer-Richard/Romer logic implies the winning citizen candidate will likewise skew taxes more heavily upon capital; this is the $\pm e^P$ term in the numerators. Second, the two jurisdictions compete with their capital tax-rates for the global pool of capital. A non-cooperative Nash equilibrium of their game induces a prisoners' dilemma for them, which pushes in the other direction toward under-taxation of capital relative to the Pareto optimum of the Ramsey Rule. The $2F_{\tau}^{*}(\tau_k, \tau^{*}_k)$ term in the right-hand side numerator would be 1 under Ramsey.Equation (3) gives the optimal capital-tax-rate policy for the domestic policymaker to choose, which, as one can see is a function of the capital tax-rate chosen abroad. The game is symmetric, so the optimal capital tax-rate for the foreign policymaker to choose looks identical from his/her point of view and, importantly, depends on the capital tax-rate chosen domestically. That is, equation (3) gives best-response functions $\tau_K = T(e^P, \tau_K^*)$ and $\tau_K^* = T^*(e^{P*}, \tau_K)$ for the foreign and the domestic policymaker. In other words, the domestic (foreign) capital-tax rate depends on the domestic (foreign) policymaker's labor-capital endowment and the foreign (domestic) capital tax rate—i.e., capital taxes are spatially interdependent. The slope of these functions, $\frac{dT}{d\tau_K^*}$ and $\frac{dT^*}{d\tau_K}$, can be either positive or negative. An increase in foreign tax-rates induces a flow of capital into the domestic economy. The domestic policymaker may use the increased tax-base to lower tax-rates or to raise them to seize the greater revenue opportunities created by the decreased elasticity of this base.

Figure 1 graphs these reaction functions assuming that $\frac{dT}{d\tau_K^*} > 0$ and $\frac{dT^*}{d\tau_K} > 0$. The illustrated comparative static shows an increase in the domestic policymaker's labor-capital endowment. This change shifts the function T outward, raising the equilibrium tax rate in both countries.

Although tax-competition models, like Persson and Tabellini's, clearly demonstrate the spatial interdependence of capital taxes, very few scholars have empirically modeled this

Figure 1. Best Response Functions (Persson and Tabellini 2000, 334)



interdependence directly.

International Interdependence and an Empirical Model of Capital-Tax Competition

We now propose and estimate a spatial error-correction model of tax competition reflecting this theoretically implied spatial interdependence. First, though, we conduct a Breusch-Pagan *LM* test to gauge the statistical evidence of spatial correlation in our raw data: the Mendoza *et al.* (1997) capital tax-rates, as updated by Volkerink and de Haan (2001). We chose our sample of 12 OECD countries—Australia, Belgium, Canada, Finland, France, Germany, Italy, Japan, Sweden, Switzerland, UK, and US—from 1966-1996 to create the largest *balanced-panel* dataset possible.[17] The *LM* statistic for these raw capital-tax data is 734.33; with a critical value of 85.96, this clearly indicates strong spatial correlation and strongly suggests a spatial model. We estimate a spatial model that reflects the theory above in two steps.

First, we estimate the spatial interdependence of capital tax-rates by regressing each country's rate on each of its (sample) economic partners' tax-rates, a deterministic time trend, and the latter interacted with each of the former. These models represent a reduced form of the Persson and Tabellini model, allowing asymmetrical influence across countries. Jointly, they also represent an estimate of the *spatial-diffusion* matrix.[18] We propose considering the predicted tax-rate in this regression as a sort of domestic *equilibrium* tax-rate that, given the set of tax-rates among its competitors, yields no further net downward pressures from global tax-competition or upward from domestic pressure for public revenue: call this a *competition-neutral* tax-rate. The interaction terms allow a country's *competition-neutral* tax-rate to change (linear-deterministically) over time as international capital mobility rises (Persson and Tabellini 1992). We then include the time *t-1* residuals from this model among regressors in the second-stage model predicting the time *t* change in domestic capital tax-rates. This is the *spatial-error-correction*.[19] Given our conception of the estimates at that stage as the *competition-neutral* rates, the residuals from stage one indicate the degree to which domestic taxes are *competition-nonneutral* or in *disequilibrium*. If the residual is positive, domestic pressures net of foreign competition remain a positive force on domestic capital-tax-rates. If the residual is negative, foreign competitive pressures net of domestic agitation for further publicly funded programs remain a negative force on domestic capital-tax-rates. In the logic of tax-competition models like that above, the domestic policymaker should in either case adjust accordingly to regain neutrality. The coefficient on that error-correction term in the second stage will indicate how rapidly such adjustment occurs.[20]

[17] As of now, all of the code we have written assumes balanced panels.

[18] Insofar as we have estimated this first stage by OLS, the estimate of the spatial-diffusion matrix is biased (see above).; we redress this deficiency below.

[19] Ideally, the time t-1 residuals used to predict time t adjustments would be based on data only from the period up to time t-1, and not beyond. We have not implemented this correctly rolling-sample strategy yet.

[20] Notice that, whereas we have allowed each country to affect the competition-neutral tax-rate of others

The first-stage coefficient-estimates are also substantively interesting. Finding a country's capital tax-rate spatially independent or exogenous would be strong evidence against competition and for national policy-autonomy. To test the independence (autonomy) hypothesis, we implement the spatial equivalent of a Granger causality test (Freeman 1983), which is simply a joint *F*-test of the hypothesis that all the spatial coefficients are zero.[21] The *LM* statistic, reported above, strongly rejected the hypothesis of no spatial correlation in the *dataset*; these *F*-tests, which are country specific, yield equally unambiguous results. No country in our sample has spatially exogenous capital tax-rates. The only cases that fail to reject at the 0.01 level are the US (p=0.0388) and UK (p=0.0173), which seems substantively intuitive.[22]

Do the sorts of equilibrium relations identified in tax-competition models generate the spatial correlation of capital tax-rates across countries seen in stage one? Out first cut at answering this question is to regress the time *t* change in the domestic capital tax-rates on the time *t-1* residuals from our first stage models. Again, we might view these residuals as a measure of the degree of *disequilibrium* or *competition nonneutrality* in a country's tax rate. A large positive residual at time *t-1* means the country's tax rate is above its *competition-neutral* level, so we would expect a negative change in time *t* to restore *neutrality*. Conversely, a large negative residual at time *t-1* means the tax rate is below *neutrality* and we would expect a positive time-*t* change. Figure 2 presents these second-stage results. As expected, a negative and statistically significant relationship exists between the time *t-1* residuals in stage one and the time *t* change in the capital tax-rate.

differently in stage one, we have, for now anyway, constrained all domestic policymakers to respond at an equal rate to net competition-nonneutrality. We have also assumed that downward pressures (net positive foreign competition) and upward pressures (net positive domestic funding demands) induce equally paced policy responses. (We thank Thomas Pluemper for emphasizing this latter point to us.)

[21] This suggests another test for spatial correlation whose properties we intend to explore in our methodological project.

[22] Sweden is next-least significant, which also seems intuitive considering its relative leadership in Scandinavia and the relative concentration of intra-regional trade. The same considerations for the *Commonwealth* rendered the UK result intuitive. The US result intuitiveness rests on its overall economic leadership and greater trade outside our sample.

Figure 2. Mendoza et al. Capital Tax Rate

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.304558298
R Square	0.092755757
Adjusted R Square	0.090303745
Standard Error	3.369857385
Observations	372

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	429.5773936	429.5773936	37.82843509	2.00494E-09
Residual	370	4201.697354	11.35593879		
Total	371	4631.274747			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.499109924	0.174720086	2.856625909	0.004523457	0.155541089	0.84267876	0.155541089	0.84267876
CT Disequilibrium	-0.895075762	0.145529357	-6.150482509	2.00494E-09	-1.181244071	-0.608907453	-1.181244071	-0.608907453

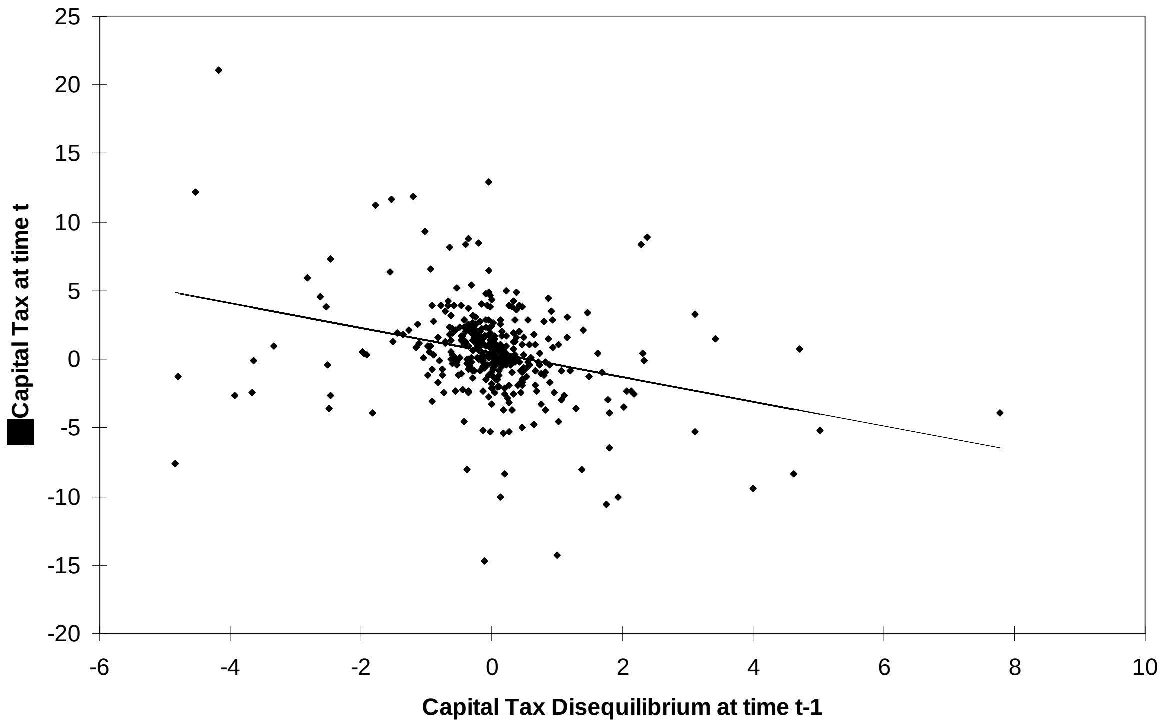


Figure 3. Devereux et al. Effective Average Corporate Tax Rate

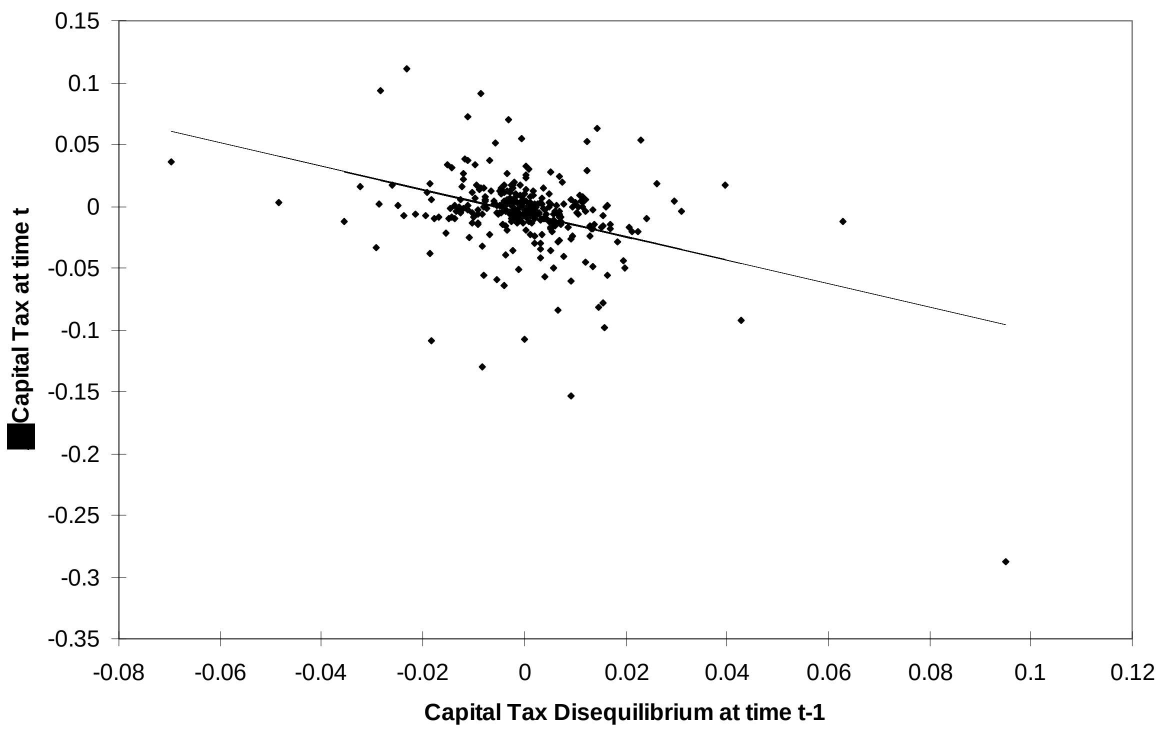
SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.391956956
R Square	0.153630255
Adjusted R Square	0.150827707
Standard Error	0.0301021
Observations	304

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.049672631	0.049672631	54.81804785	1.32548E-12
Residual	302	0.273653208	0.000906136		
Total	303	0.323325839			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.005644645	0.001726558	-3.269305787	0.001202668	-0.009042254	-0.002247037	-0.009042254	-0.002247037
CT Disequilibrium	-0.950574682	0.128388008	-7.403921113	1.32548E-12	-1.203223145	-0.697926219	-1.203223145	-0.697926219



Next, we offer some preliminary robustness checks. Some scholars criticize Mendoza *et al.* tax ratios, so we consider also the *effective average corporate tax-rates* of Devereux, Griffith, and Klemm (2002).[23] Their approach is similar to the well-known *cost-of-capital* method of King and Fullerton (1984).[24] Our results with Devereux *et al.* corporate tax-rates are very similar to those with Mendoza *et al*. No sample countries have tax rates independent of their (sample) economic partners' tax-rates, and the time *t-1* residuals from the stage one spatial-model predict time *t* changes in corporate tax-rates (Fig. 3).

As the preceding methodological sections demonstrated, the slopes of the best-response functions in Figure 1 are unidentified in the reduced form empirical models reported in Figures 2-3. However, this does not hinder the particular use to which we employ the estimates here because individual-coefficient identification is not necessarily required for prediction. In other words, our regressions offer identified predictions of the *competition-neutral* capital tax-rate, which are all the error-correction model needs. Nevertheless, since the slopes of the best-response functions are of substantive interest, we also estimate our stage one spatial regression using the spatial two-stage least-squares approach suggested in the preceding methodological sections. That domestic political, institutional, and structural factors partly determine each country's capital tax-rate seems likely (see, *e.g.*, Swank 2002), and that such domestic factors are relatively exogenous of current capital tax-rates also seems likely. If so, these variables could supply valid instruments or at least "quasi-instruments" with good "Bartels Ratios." Accordingly, we estimate our spatial regression treating each right-hand-side capital tax-rate as endogenous and using (unweighted) debt

[23] Mendoza et al. calculate their rates using the total tax payment as a proportion of some conventional measure of the tax base. For the capital tax rate, they use the operating surplus of the economy as the tax base. Devereux et al. point out that, if this measure were identical to the true tax base, as defined by the tax system, the Mendoza et al. rate would equal the statutory tax rate. Differences between the measured and true tax base reflect the fact that legislators deliberately define the tax base to be smaller or larger than the conventional base. Devereux et al. point out that current tax liabilities, particularly for corporations, reflect: 1) the history of investment, which determines allowances in the current period 2) tax liabilities in multiple jurisdictions, 3) the history of losses, which can be carried forward, and 4) the history of the tax system. In these ways, the Mendoza et al. rates are "backward looking" and unlikely to affect future investments decisions (Devereux et al. 2002, 468-9).

[24] These approaches infer the "cost of capital" from a net present value calculation, and then use this cost to compute effective tax rates (for details, see Devereux et al. 2002, 461).

levels and government partisanship (center of gravity) as exogenous instruments. Overall, the results for the spatial error-correction model do not change much (see Figure 4).

Figure 4. Mendoza et al. Capital Tax Rates (2SLS Results)

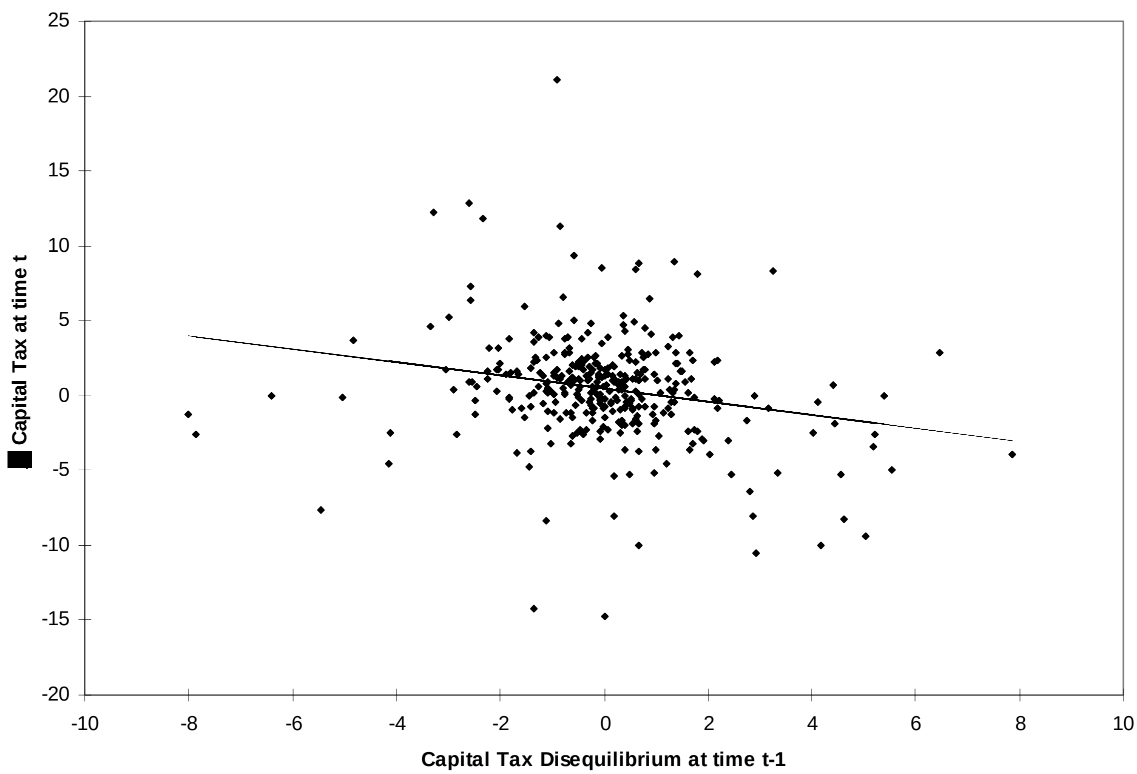
SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.222588406
R Square	0.049545599
Adjusted R Square	0.046798621
Standard Error	3.502860754
Observations	348

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	221.3072494	221.3072494	18.03640145	2.78861E-05
Residual	346	4245.431578	12.27003346		
Total	347	4466.738828			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.471034484	0.187773046	2.508530879	0.012580273	0.101713828	0.840355141	0.101713828	0.840355141
Error	-0.441204132	0.103887818	-4.246928473	2.78861E-05	-0.645535466	-0.236872797	-0.645535466	-0.236872797



Finally, we re-estimate our original spatial-error correction model (see Figure 2) controlling for a number of additional variables and using standard methods for analyzing *TSCS* data. Specifically, we lag the dependent variable, include fixed effects, report *PCSE*, and control for lagged debt, unemployment, real-GDP growth, trade openness, inflation, and government partisanship (factors Swank 2002 identified as important). Table 5 reports results. The lagged dependent variable, spatial error-correction term, and growth variable all receive correctly signed and statistically significant coefficients. The debt variable is correctly signed and borderline significant. Partisanship is also correctly signed, but insignificant.

Table 5. Multivariate Regression Results

	Coef.	PCSE	z	P>|z|
Lagged DV	.3169866	.0837531	3.78	0.000
Error Correction Term	-1.147844	.1958894	-5.86	0.000
Debt	2.200018	1.342113	1.64	0.101
Unemployment	-.1507454	.1171767	-1.29	0.198
GDP Growth	.4563691	.0802553	5.69	0.000
Trade Openness	3.835564	3.123282	1.23	0.219
Inflation	.0369919	.0724842	0.51	0.610
Partisan Center of Gravity	-.1430701	.160376	-0.89	0.372

Substantive-Application Conclusions

Most social scientists realize that the TSCS data they analyze are spatially interdependent—i.e., variables correlate across space or other non-temporal dimension. Few, however, address the spatial relationships in their data seriously enough to model them further than employing PCSE. In this paper, we have argued direct modeling of spatial dependence is superior, even if one has little substantive interest in spatial relations. Direct modeling of spatial dependence increases efficiency and, in some cases, is necessary to avoid sizable bias and inconsistency in estimated coefficients, even those on non-spatial regressors. For comparative and international political economists, globalization makes these methodological issues increasingly central. Put simply, globalization causes spatial interdependence; indeed, globalization essentially *is* interdependence.

We have begun to explore a new way to model spatial equilibrium relationships—a spatial error-correction model—and applied this technique in an analysis of capital tax rates. That others have not modeled the spatial relationships in capital tax-rates is surprising given that most, if not all, theoretical models of tax competition imply spatial interdependence. Our analysis finds strong evidence of spatial correlation in OECD capital tax-rates. Moreover, this dependence seems to suggest the existence of competition-neutral capital tax-rates generating a sort of equilibrium cross-national relationship in rates of capital taxation that is driven, in part, by international capital mobility and tax competition.

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Appendix

Table A1. OLS, N=5

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.5)*W*Y + EPS
Est. Model Y= b1*X + b2*ETA + b3*X*ETA
Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	1.10282	0.16663	0.61566	1.41732	1.0968	0.12375	0.80864	1.49079	1.11433	0.10177	0.92298	1.3807	1.11175	0.07475	0.88602	1.29935
	se(b1)	0.1412	0.02275	0.10495	0.20342	0.11323	0.01355	0.08458	0.15481	0.09802	0.00912	0.07768	0.12398	0.06818	0.00519	0.05727	0.08677
	b2	2.04019	0.28127	1.47876	2.6875	2.02496	0.24187	1.37457	2.56737	1.97567	0.21408	1.62405	2.61396	1.99656	0.19465	1.58685	2.41872
	se(b2)	0.13677	0.02576	0.08124	0.21023	0.11435	0.01648	0.07999	0.16659	0.09714	0.01215	0.07583	0.1257	0.06809	0.00545	0.05469	0.0822
	b3	1.12873	0.21617	0.61123	1.9194	1.12463	0.15682	0.69152	1.62438	1.08498	0.10608	0.82034	1.40972	1.10273	0.09525	0.90943	1.39589
	se(b3)	0.14372	0.03257	0.08542	0.23971	0.11874	0.02125	0.0758	0.17928	0.09998	0.01335	0.07228	0.13838	0.06902	0.00705	0.05196	0.08776
	b4																
	se(b4)																
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	1.17439	0.32667	0.54236	3.15535	1.15554	0.34934	0.74119	3.86233	1.11649	0.15312	0.83669	1.5591	1.16481	0.1907	0.83686	2.02101
	se(b1)	0.17493	0.06312	0.10039	0.48153	0.14053	0.05968	0.07954	0.55787	0.11738	0.03184	0.07357	0.24966	0.08919	0.03693	0.05716	0.27491
	b2	2.21085	0.96412	1.07984	8.41137	2.27655	1.30706	0.95887	11.3067	2.06303	0.73519	1.017	6.48009	2.27167	1.01261	1.01282	7.95838
	se(b2)	0.18026	0.07641	0.08724	0.56426	0.14346	0.07474	0.08164	0.72149	0.11787	0.03319	0.06696	0.278	0.08883	0.03508	0.05345	0.25481
	b3	1.12682	0.33309	0.55804	2.56987	1.13487	0.35418	0.767	3.78218	1.1165	0.19586	0.67519	2.15856	1.14171	0.19365	0.88082	2.43062
	se(b3)	0.19128	0.08352	0.09601	0.61238	0.14861	0.07456	0.0803	0.70415	0.12141	0.03566	0.06615	0.29497	0.09003	0.03587	0.05387	0.27484
	b4																
	se(b4)																
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	0.98113	0.12625	0.75577	1.37953	0.99808	0.103	0.71249	1.2831	1.01925	0.09024	0.83298	1.22508	0.99653	0.06598	0.87173	1.12582
	se(b1)	0.12209	0.01501	0.09361	0.17876	0.098	0.00929	0.0775	0.12544	0.08486	0.00926	0.06335	0.10819	0.05832	0.00349	0.04856	0.06856
	b2	1.00033	0.18628	0.57193	1.49866	1.03324	0.15959	0.75549	1.52143	1.01203	0.17633	0.63803	1.67544	1.00081	0.15153	0.74288	1.51479
	se(b2)	0.12306	0.02365	0.07515	0.19917	0.09805	0.01464	0.06764	0.13406	0.08634	0.01106	0.06323	0.12419	0.05865	0.00557	0.04701	0.07674
	b3	1.00716	0.14896	0.71255	1.83957	0.98541	0.09439	0.77473	1.28669	1.00476	0.10554	0.72619	1.33835	0.99679	0.07628	0.82145	1.16282
	se(b3)	0.12908	0.03045	0.07588	0.24052	0.10104	0.01628	0.06832	0.16436	0.08793	0.01425	0.06056	0.13465	0.0587	0.00635	0.04276	0.07718
	b4																
	se(b4)																

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.1)*W*Y + EPS
Est. Model Y= b1*X + b2*ETA + b3*X*ETA
Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	0.99616	0.11259	0.6851	1.31529	0.99615	0.08474	0.73012	1.26115	1.01081	0.07299	0.84791	1.20978	1.00575	0.04261	0.86346	1.11342
	se(b1)	0.10601	0.01327	0.08196	0.14045	0.08423	0.00727	0.0679	0.10516	0.07286	0.00529	0.05917	0.09147	0.05093	0.00249	0.04493	0.05705
	b2	1.12108	0.10854	0.85635	1.41815	1.12184	0.08906	0.90471	1.36313	1.10803	0.07706	0.90514	1.3066	1.10755	0.06129	0.89874	1.26231
	se(b2)	0.10279	0.01721	0.06399	0.15193	0.08515	0.01073	0.06215	0.116	0.07229	0.00873	0.05787	0.10097	0.05093	0.00383	0.04129	0.06283
	b3	1.00908	0.1277	0.63971	1.35968	1.01807	0.09805	0.74046	1.36376	1.00534	0.06904	0.81077	1.19419	1.00747	0.05118	0.87645	1.13251
	se(b3)	0.10814	0.02347	0.06088	0.1956	0.08852	0.01546	0.0633	0.13924	0.07446	0.0101	0.05605	0.10204	0.05164	0.00534	0.03831	0.06441
	b4																
	se(b4)																
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	1.0045	0.1047	0.69294	1.25096	0.99647	0.08188	0.75848	1.16398	1.00313	0.07253	0.8337	1.14125	1.00662	0.0468	0.82928	1.1117
	se(b1)	0.10514	0.01084	0.0835	0.14985	0.08439	0.00769	0.06919	0.10592	0.07356	0.00636	0.06064	0.08837	0.0512	0.00239	0.04556	0.05634
	b2	1.10444	0.12748	0.83199	1.3808	1.11626	0.10691	0.81318	1.36544	1.09806	0.084	0.87924	1.28416	1.12152	0.06449	0.96948	1.2685
	se(b2)	0.10761	0.02113	0.06698	0.168	0.08548	0.01205	0.06334	0.12487	0.0739	0.00885	0.0552	0.09614	0.05128	0.00437	0.04142	0.06262
	b3	0.99142	0.11591	0.73357	1.28325	0.99941	0.08667	0.79537	1.2284	0.99825	0.07052	0.83838	1.1586	1.00124	0.0527	0.86939	1.13947
	se(b3)	0.11434	0.02608	0.07334	0.20285	0.08878	0.01483	0.06104	0.12571	0.07617	0.01107	0.05452	0.10701	0.05198	0.00548	0.04192	0.06921
	b4																
	se(b4)																
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	0.98026	0.10342	0.79499	1.19779	0.99227	0.09119	0.77083	1.20235	1.01827	0.07215	0.85552	1.19782	0.99902	0.05076	0.89445	1.11257
	se(b1)	0.10707	0.01145	0.08075	0.13677	0.08493	0.00743	0.06978	0.1076	0.07311	0.00673	0.0572	0.09436	0.05084	0.00244	0.04441	0.0573
	b2	0.98801	0.12021	0.64851	1.26754	1.0086	0.08002	0.79192	1.22257	1.01164	0.08386	0.82659	1.23352	1.00093	0.05003	0.8787	1.1387
	se(b2)	0.10806	0.02064	0.07144	0.17571	0.08499	0.01232	0.05869	0.11588	0.07449	0.00925	0.05476	0.09905	0.05114	0.0046	0.04238	0.06569
	b3	1.00671	0.11919	0.68671	1.47354	0.98355	0.0754	0.82534	1.18537	1.00204	0.07869	0.80609	1.24268	0.99596	0.05355	0.8619	1.1069
	se(b3)	0.11337	0.02634	0.06639	0.21521	0.0877	0.0145	0.05606	0.14432	0.07586	0.01191	0.0495	0.11183	0.05121	0.00556	0.03586	0.06607
	b4																
	se(b4)																

Table A2. GPP, N=5

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.5)*W*Y + EPS
Est. Model Y= b1*X + b2*ETA + b3*X*ETA + b4*W*Y (GPP)
Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	0.97687	0.11305	0.6683	1.36643	0.9759	0.08411	0.67803	1.1615	0.98709	0.06972	0.79427	1.14839	0.98387	0.04365	0.87365	1.08083
	se(b1)	0.10765	0.01321	0.08334	0.14485	0.0849	0.00752	0.06866	0.11081	0.07315	0.0057	0.05915	0.09235	0.05128	0.00262	0.04484	0.05819
	b2	0.85336	0.17871	0.32817	1.35556	0.84273	0.13695	0.5395	1.22715	0.8077	0.1209	0.52814	1.10777	0.81382	0.07883	0.60475	1.00008
	se(b2)	0.17858	0.0356	0.10156	0.28547	0.14108	0.0233	0.0915	0.21581	0.11788	0.01681	0.08829	0.16997	0.08403	0.00827	0.06353	0.111
	b3	0.99043	0.13032	0.65973	1.27621	0.9969	0.09856	0.78709	1.34646	0.99062	0.07638	0.82932	1.23754	0.98832	0.05723	0.82794	1.12564
	se(b3)	0.11036	0.02494	0.06205	0.20427	0.08948	0.01543	0.06362	0.13963	0.07459	0.01014	0.05537	0.10161	0.05198	0.00545	0.03847	0.06546
	b4	0.57534	0.08405	0.32408	0.80704	0.58547	0.0626	0.40557	0.74806	0.5895	0.05563	0.45393	0.74799	0.58847	0.04043	0.47445	0.67399
	se(b4)	0.0705	0.01463	0.03998	0.11153	0.05574	0.01047	0.03381	0.09407	0.04713	0.00693	0.03467	0.06931	0.0334	0.00345	0.02248	0.04248
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	0.99978	0.16385	0.69612	1.67914	0.96857	0.11848	0.57392	1.23019	0.98291	0.09716	0.73547	1.26804	0.98479	0.07749	0.7869	1.19326
	se(b1)	0.13855	0.03064	0.10057	0.33621	0.10859	0.0211	0.07739	0.21251	0.09358	0.01567	0.06937	0.14222	0.06865	0.01856	0.05094	0.18069
	b2	0.93295	0.27926	0.49015	2.06949	0.88902	0.18224	0.34292	1.33954	0.8699	0.1645	0.48118	1.47919	0.89583	0.14724	0.60737	1.42976
	se(b2)	0.2337	0.07144	0.1264	0.66506	0.17984	0.04691	0.10125	0.41571	0.15031	0.02882	0.10674	0.25925	0.10923	0.0315	0.07333	0.30411
	b3	0.96943	0.18151	0.49359	1.56322	0.98025	0.13286	0.74739	1.47295	0.99013	0.11707	0.68541	1.31938	0.97167	0.09046	0.77769	1.30958
	se(b3)	0.14919	0.03912	0.08959	0.30173	0.1137	0.02648	0.07234	0.21651	0.0966	0.01751	0.06286	0.15288	0.06927	0.01714	0.04945	0.16146
	b4	0.53173	0.17448	0.02023	0.8626	0.55285	0.15798	0.13429	0.90397	0.5461	0.142	0.11805	0.85517	0.55751	0.14905	0.1355	0.90431
	se(b4)	0.08829	0.02563	0.03825	0.14847	0.06791	0.01596	0.01686	0.10925	0.05956	0.01328	0.02701	0.08756	0.03984	0.00846	0.01732	0.06296
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	0.97184	0.12782	0.75536	1.3785	0.9907	0.09956	0.7069	1.26545	1.00822	0.09131	0.8141	1.23214	0.99015	0.06595	0.85971	1.12388
	se(b1)	0.12159	0.01545	0.09299	0.17727	0.09741	0.00926	0.07766	0.12485	0.08391	0.00857	0.06446	0.10878	0.05778	0.0036	0.04866	0.06805
	b2	1.07517	0.236	0.69222	1.92597	1.06325	0.21494	0.56449	1.73689	1.08809	0.19475	0.65516	1.61928	1.0301	0.12558	0.66295	1.29171
	se(b2)	0.18747	0.04131	0.12643	0.3743	0.15082	0.02432	0.09515	0.23473	0.12713	0.01582	0.08428	0.16432	0.08666	0.00833	0.06688	0.10747
	b3	0.99606	0.15344	0.64257	1.83784	0.97619	0.09624	0.75857	1.26176	0.99151	0.10952	0.70777	1.32279	0.99023	0.07445	0.81654	1.16065
	se(b3)	0.12913	0.03047	0.0776	0.23984	0.10077	0.01607	0.06878	0.16307	0.08712	0.01334	0.05892	0.12701	0.05819	0.00626	0.04282	0.07712
	b4	-0.1053	0.26141	-0.8693	0.49485	-0.0495	0.24037	-0.6761	0.35281	-0.0993	0.24778	-0.6919	0.55091	-0.0536	0.21393	-0.5534	0.35442
	se(b4)	0.14222	0.02522	0.08431	0.22257	0.10941	0.01696	0.0743	0.14787	0.09452	0.01379	0.06035	0.13375	0.06486	0.00804	0.0457	0.08497

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.1)*W*Y + EPS
Est. Model Y= b1*X + b2*ETA + b3*X*ETA + b4*W*Y (GPP)
Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	0.98985	0.11356	0.68452	1.35918	0.99085	0.08446	0.71417	1.21496	1.00647	0.07094	0.83833	1.18498	1.00211	0.04171	0.87421	1.10917
	se(b1)	0.10619	0.01314	0.08229	0.14092	0.08399	0.00731	0.06795	0.10618	0.0724	0.00545	0.05889	0.0917	0.05069	0.00249	0.04436	0.05678
	b2	1.02123	0.19605	0.54679	1.60609	1.00436	0.15562	0.67602	1.41271	0.95856	0.12926	0.69165	1.33703	0.96832	0.08564	0.741	1.17249
	se(b2)	0.16771	0.03214	0.09953	0.25845	0.13318	0.02107	0.08533	0.20302	0.11199	0.01572	0.08474	0.15995	0.07971	0.00748	0.06085	0.10335
	b3	1.00118	0.12929	0.6133	1.31588	1.01211	0.09784	0.72426	1.35095	1.00593	0.07079	0.81964	1.21131	1.00529	0.05168	0.8706	1.12554
	se(b3)	0.10891	0.02425	0.06215	0.20153	0.08857	0.01545	0.06258	0.13939	0.07418	0.01016	0.05439	0.10173	0.05151	0.00539	0.03815	0.06537
	b4	0.08526	0.15187	-0.2633	0.47978	0.10602	0.12068	-0.2929	0.39633	0.13452	0.09332	-0.1019	0.36	0.12546	0.05846	-0.0385	0.26312
	se(b4)	0.11566	0.02172	0.06744	0.18014	0.09188	0.01565	0.06261	0.14601	0.07709	0.01047	0.05823	0.10814	0.05492	0.0049	0.04237	0.06777
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	0.99516	0.10528	0.66813	1.24943	0.99015	0.07944	0.76069	1.16066	0.99946	0.07365	0.82854	1.14675	1.00175	0.04751	0.83001	1.12244
	se(b1)	0.1055	0.01072	0.08323	0.1509	0.08418	0.00752	0.06942	0.10442	0.07325	0.00638	0.06086	0.08828	0.0509	0.00235	0.04547	0.05651
	b2	1.02095	0.1969	0.6295	1.56755	0.99414	0.14758	0.52805	1.37851	0.97892	0.13782	0.66234	1.39776	0.9815	0.08423	0.80258	1.33675
	se(b2)	0.17319	0.03305	0.0954	0.26032	0.13555	0.02047	0.09044	0.21309	0.11574	0.01503	0.08679	0.15595	0.07942	0.00767	0.06087	0.10205
	b3	0.98378	0.10925	0.72417	1.28928	0.99717	0.08625	0.81512	1.2353	0.99596	0.07143	0.82704	1.14857	0.99711	0.0519	0.86237	1.14184
	se(b3)	0.11479	0.02522	0.07331	0.19469	0.08866	0.01476	0.06226	0.12653	0.07604	0.01099	0.05515	0.10788	0.05172	0.00545	0.04145	0.06922
	b4	0.07376	0.16908	-0.6437	0.36286	0.10604	0.11563	-0.2313	0.38922	0.10826	0.10946	-0.1974	0.37488	0.12386	0.0737	-0.0996	0.32005
	se(b4)	0.1196	0.02307	0.07707	0.19492	0.09398	0.01354	0.06963	0.12539	0.08087	0.01086	0.0631	0.11215	0.05436	0.00486	0.04228	0.06903
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	0.98004	0.10303	0.79454	1.20256	0.99071	0.0897	0.78121	1.20259	1.01601	0.07278	0.85107	1.21151	0.99829	0.05074	0.89381	1.1122
	se(b1)	0.10771	0.01169	0.08095	0.13493	0.08508	0.00744	0.06993	0.1084	0.07325	0.00672	0.05853	0.09474	0.0509	0.00245	0.04444	0.05738
	b2	1.0186	0.19925	0.54273	1.5929	1.01838	0.15686	0.69868	1.47201	1.0297	0.15122	0.70486	1.46631	1.00618	0.08388	0.80505	1.25818
	se(b2)	0.16934	0.03537	0.11349	0.3109	0.13444	0.02117	0.08293	0.19709	0.11344	0.01494	0.07658	0.15521	0.0784	0.00717	0.06219	0.09744
	b3	1.00305	0.11851	0.68188	1.4618	0.98057	0.07724	0.81471	1.1848	0.99848	0.08055	0.76257	1.23289	0.99556	0.05399	0.86075	1.1109
	se(b3)	0.11459	0.02623	0.06631	0.21695	0.08818	0.01455	0.05689	0.14414	0.07618	0.01191	0.04936	0.11091	0.0513	0.00556	0.03588	0.06591
	b4	-0.0357	0.14381	-0.4613	0.3476	-0.014	0.14127	-0.4712	0.25684	-0.0168	0.11654	-0.3417	0.23595	-0.0058	0.07959	-0.1944	0.21082
	se(b4)	0.13086	0.02129	0.09415	0.19621	0.10074	0.01559	0.06312	0.13615	0.08482	0.01044	0.06043	0.11625	0.05915	0.00539	0.04798	0.07415

Table A3. OLS, N=20

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.5)*W*Y + EPS
Est. Model Y= b1*X + b2*ETA + b3*X*ETA
Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0
N = 20

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
	b1	1.03591	0.06402	0.8222	1.20689	1.02219	0.05526	0.88745	1.18756	1.02308	0.03971	0.92451	1.1207	1.03123	0.02882	0.96496	1.10351
	se(b1)	0.05976	0.0042	0.05331	0.07947	0.04797	0.00334	0.0435	0.06905	0.04105	0.00227	0.03715	0.0477	0.02886	0.00108	0.0268	0.03246
Wij = [(1/(N-1))-	b2	2.04032	0.18536	1.45389	2.47843	2.02272	0.18145	1.58091	2.78416	1.97245	0.15	1.64811	2.37843	2.00587	0.12479	1.75873	2.46017
0.1, (1/(N-	se(b2)	0.05935	0.0092	0.04345	0.09121	0.04856	0.00669	0.03422	0.06867	0.04082	0.00415	0.03312	0.05064	0.02869	0.00262	0.02322	0.03718
1))+0.1], , i <> j;	b3	1.02566	0.07008	0.87975	1.19139	1.03416	0.0586	0.89934	1.19643	1.02398	0.04592	0.90671	1.17997	1.02311	0.03228	0.95982	1.12319
otherwise Wij = 0	se(b3)	0.06105	0.01009	0.04266	0.0966	0.04959	0.00757	0.03589	0.07453	0.04157	0.00466	0.03255	0.05506	0.0289	0.00265	0.0234	0.03898
	b4																
	se(b4)																
	b1	1.05866	0.20887	0.74532	2.3537	1.03033	0.11676	0.76358	1.43484	1.06129	0.17388	0.85146	2.04242	1.04754	0.131	0.82445	1.63266
	se(b1)	0.13915	0.07066	0.08402	0.54345	0.10427	0.03418	0.06684	0.24392	0.10167	0.06804	0.06059	0.64509	0.07226	0.04123	0.04036	0.34608
Wij = [(1/(N-1))-	b2	2.25334	1.11706	0.80328	7.85497	2.10778	0.83361	0.99684	6.09506	2.32642	1.99995	0.89082	19.977	2.42544	1.40946	1.11251	10.9402
0.5, (1/(N-	se(b2)	0.1378	0.06402	0.07616	0.49225	0.10408	0.03088	0.06805	0.24922	0.09989	0.06135	0.06001	0.57874	0.07261	0.04231	0.03962	0.34566
1))+0.5], , i <> j;	b3	1.0846	0.2599	0.36977	2.02164	1.03529	0.18089	0.63308	1.79227	1.04892	0.14979	0.72854	1.69358	1.04142	0.13119	0.80984	1.47649
otherwise Wij = 0	se(b3)	0.14136	0.06842	0.07584	0.4976	0.10616	0.03228	0.06808	0.25886	0.10156	0.06197	0.05886	0.57984	0.07325	0.04242	0.0404	0.3389
	b4																
	se(b4)																
	b1	1.01873	0.12025	0.77026	1.28177	1.02868	0.08811	0.85076	1.3218	1.02368	0.07359	0.84287	1.30132	1.02402	0.06104	0.89572	1.17675
	se(b1)	0.10154	0.01716	0.07281	0.16088	0.08121	0.0144	0.05795	0.13982	0.06907	0.00857	0.05204	0.10452	0.04842	0.00668	0.03708	0.07364
Wij = u[-0.5, 0.5],	b2	0.99985	0.20614	0.65494	1.62324	1.03248	0.21091	0.72655	2.0321	1.03201	0.20141	0.65756	1.68806	1.00582	0.20305	0.72768	1.73059
, i <> j; otherwise	se(b2)	0.10009	0.01896	0.07173	0.15781	0.08123	0.0152	0.05573	0.13559	0.06966	0.00961	0.04509	0.10372	0.04836	0.00726	0.03107	0.07566
Wij = 0	b3	1.00993	0.12447	0.77065	1.38928	1.014	0.11971	0.70202	1.37637	1.02218	0.09398	0.80729	1.2926	1.01447	0.08413	0.79862	1.25259
	se(b3)	0.10225	0.01876	0.07295	0.14967	0.08304	0.01565	0.06162	0.14317	0.0709	0.01011	0.04375	0.10386	0.04901	0.00744	0.03262	0.07524
	b4																
	se(b4)																

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.1)*W*Y + EPS
Est. Model Y= b1*X + b2*ETA + b3*X*ETA
Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0
N = 20

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
	b1	1.0083	0.05649	0.81668	1.13521	0.99899	0.04651	0.91	1.13364	0.99952	0.03455	0.90635	1.07677	1.00616	0.02499	0.94229	1.07758
	se(b1)	0.05214	0.00313	0.04639	0.06456	0.04181	0.00212	0.0377	0.05263	0.03611	0.00163	0.03289	0.04062	0.02517	0.00067	0.02374	0.02667
Wij = [(1/(N-1))-	b2	1.12401	0.05989	0.96857	1.3094	1.11553	0.05187	0.9796	1.27715	1.10459	0.04006	1.02085	1.21936	1.11445	0.02735	1.04152	1.17484
0.1, (1/(N-	se(b2)	0.05189	0.00851	0.03738	0.0803	0.04239	0.00594	0.02813	0.05706	0.03595	0.00392	0.02879	0.04574	0.02505	0.00245	0.02073	0.03432
1))+0.1], , i <> j;	b3	1.00302	0.05431	0.87761	1.18947	1.00777	0.04419	0.89187	1.13235	1.00257	0.03329	0.90112	1.10808	0.99979	0.02303	0.95701	1.05417
otherwise Wij = 0	se(b3)	0.05338	0.00931	0.03616	0.08504	0.04327	0.0065	0.0295	0.05752	0.03661	0.00433	0.0283	0.04736	0.02524	0.00251	0.02065	0.03598
	b4																
	se(b4)																
	b1	1.00157	0.05616	0.86232	1.15468	1.0021	0.0454	0.83998	1.124	1.00105	0.03478	0.91874	1.06296	0.99226	0.02484	0.93288	1.04734
	se(b1)	0.05336	0.00281	0.04777	0.06179	0.04296	0.00203	0.03919	0.04931	0.03726	0.00164	0.03431	0.04137	0.02608	0.0007	0.0244	0.02747
Wij = [(1/(N-1))-	b2	1.10712	0.07267	0.94555	1.32331	1.11434	0.06405	0.96547	1.28126	1.11401	0.05153	0.99302	1.26486	1.11008	0.04921	0.99984	1.23992
0.5, (1/(N-	se(b2)	0.05379	0.00885	0.03504	0.07644	0.04335	0.00491	0.03354	0.05472	0.03711	0.00416	0.0278	0.04855	0.02616	0.00201	0.02132	0.03493
1))+0.5], , i <> j;	b3	1.00785	0.0562	0.83743	1.11103	1.00251	0.03993	0.89101	1.08607	1.00045	0.03751	0.92048	1.08729	1.00101	0.03141	0.90074	1.06645
otherwise Wij = 0	se(b3)	0.05491	0.00934	0.03774	0.08145	0.04417	0.00524	0.03431	0.05595	0.03774	0.00465	0.02881	0.05437	0.02639	0.00211	0.02174	0.0342
	b4																
	se(b4)																
	b1	0.99268	0.05277	0.84485	1.09961	0.99737	0.04015	0.8972	1.10295	0.99997	0.03735	0.91935	1.10666	1.00236	0.02405	0.93979	1.05668
	se(b1)	0.05313	0.00333	0.04595	0.06137	0.04305	0.00196	0.03763	0.04846	0.03691	0.00159	0.0327	0.04346	0.02605	0.0007	0.02449	0.02807
Wij = u[-0.5, 0.5],	b2	0.99941	0.0544	0.86318	1.12191	1.00529	0.04484	0.88652	1.09411	1.0071	0.04342	0.88357	1.11792	0.9987	0.03648	0.91991	1.08555
, i <> j; otherwise	se(b2)	0.05271	0.00812	0.03265	0.07845	0.04334	0.00623	0.03426	0.06056	0.03736	0.00449	0.02777	0.05065	0.02606	0.00232	0.02188	0.03236
Wij = 0	b3	0.99394	0.05075	0.86575	1.12285	0.99572	0.0472	0.87504	1.10721	1.00011	0.03409	0.91296	1.06997	1.00038	0.02421	0.93793	1.0776
	se(b3)	0.05396	0.00881	0.03308	0.08135	0.04434	0.00657	0.03461	0.06198	0.03807	0.00506	0.02743	0.05048	0.02642	0.00255	0.02173	0.03466
	b4																
	se(b4)																

Table A4. GPP, N=20

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.5)*W*Y + EPS

Est. Model Y= b1*X + b2*ETA + b3*X*ETA + b4*W*Y (GPP)

Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0

N = 20

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	1.00584	0.05982	0.8383	1.15398	0.99314	0.04908	0.89906	1.11552	0.99419	0.03497	0.90054	1.07904	1.00132	0.02575	0.93361	1.07269
	se(b1)	0.05505	0.00343	0.04839	0.06899	0.04421	0.00241	0.03888	0.05562	0.038	0.00166	0.03494	0.04218	0.02656	0.0008	0.02486	0.02886
	b2	0.83757	0.1556	0.42803	1.276	0.86361	0.13053	0.56566	1.38564	0.83267	0.1092	0.51099	1.08567	0.8457	0.07851	0.5985	1.02758
	se(b2)	0.15815	0.03343	0.06447	0.25881	0.12692	0.02583	0.08165	0.24187	0.10708	0.01692	0.0784	0.15077	0.07358	0.00774	0.05537	0.0996
	b3	1.0013	0.05973	0.86173	1.18815	1.00452	0.04801	0.88717	1.10669	0.99983	0.03851	0.90646	1.12871	0.99364	0.02542	0.94139	1.0621
	se(b3)	0.05626	0.00924	0.04049	0.08554	0.04571	0.00653	0.03217	0.05999	0.0385	0.00428	0.0297	0.04905	0.02661	0.00248	0.02167	0.03677
	b4	0.58204	0.07254	0.37477	0.78633	0.57009	0.06995	0.3682	0.71791	0.57628	0.06151	0.44945	0.75565	0.57691	0.04577	0.47881	0.71455
	se(b4)	0.07154	0.01503	0.04417	0.11369	0.05839	0.01202	0.03576	0.09931	0.05074	0.00762	0.03421	0.0752	0.03427	0.00393	0.02602	0.04945
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	1.01667	0.1582	0.66308	1.72656	1.00174	0.11119	0.71937	1.39826	1.02126	0.1302	0.81241	1.69535	1.01194	0.10984	0.8086	1.46299
	se(b1)	0.13586	0.06718	0.0825	0.51464	0.10179	0.03234	0.0671	0.23997	0.09936	0.06469	0.06065	0.60763	0.07031	0.04023	0.04038	0.3397
	b2	1.20639	0.55059	0.341	4.57885	1.18885	0.46903	0.37052	2.71598	1.19531	0.59293	0.45786	4.60117	1.20156	0.51263	0.49879	4.69674
	se(b2)	0.318	0.15336	0.14849	1.36814	0.24388	0.08749	0.12355	0.69024	0.22755	0.16048	0.11901	1.51547	0.16453	0.09618	0.09075	0.83118
	b3	1.05273	0.2472	0.12576	2.0398	1.00392	0.17065	0.62636	1.57943	1.00683	0.15514	0.33626	1.51089	1.00912	0.12143	0.6731	1.41778
	se(b3)	0.13788	0.06428	0.07428	0.4942	0.10366	0.03047	0.06701	0.25511	0.09928	0.05908	0.05839	0.54799	0.07124	0.0413	0.04009	0.33209
	b4	0.41336	0.25942	-0.6946	0.85091	0.38961	0.26383	-0.4094	0.78961	0.42115	0.23172	-0.1763	0.78236	0.43003	0.2432	-0.3656	0.80912
	se(b4)	0.13092	0.03149	0.0584	0.2557	0.1091	0.02901	0.0561	0.20036	0.0918	0.02093	0.05367	0.1444	0.06407	0.01457	0.03474	0.09842
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	1.01162	0.11623	0.78008	1.27633	1.02409	0.08865	0.85117	1.31083	1.01702	0.07462	0.84214	1.3032	1.01905	0.05915	0.89208	1.18388
	se(b1)	0.10093	0.01703	0.07191	0.16109	0.08076	0.01416	0.05797	0.1396	0.06864	0.00847	0.05204	0.10402	0.0481	0.00639	0.03674	0.07076
	b2	1.4171	0.49733	0.68578	3.04286	1.33515	0.3883	0.57062	2.19359	1.33575	0.43075	0.59144	2.84515	1.241	0.37739	0.50487	3.09462
	se(b2)	0.23426	0.04951	0.13523	0.35104	0.18525	0.0374	0.11967	0.29018	0.16047	0.0286	0.1005	0.24413	0.10702	0.01821	0.07167	0.17563
	b3	0.99779	0.12305	0.77501	1.33133	1.00791	0.11496	0.70985	1.33927	1.0136	0.09234	0.79132	1.28308	1.01024	0.08279	0.79991	1.23
	se(b3)	0.10178	0.01876	0.07233	0.1503	0.08261	0.01555	0.0615	0.14325	0.07051	0.00997	0.0437	0.10336	0.0487	0.00717	0.03262	0.07289
	b4	-0.4657	0.59998	-2.225	0.38139	-0.3443	0.45282	-1.7564	0.55995	-0.3551	0.54872	-2.5201	0.50433	-0.2906	0.48161	-2.1589	0.6562
	se(b4)	0.21256	0.05077	0.1238	0.33945	0.16487	0.03342	0.09082	0.24595	0.14365	0.03301	0.07801	0.24289	0.0972	0.02061	0.05107	0.16797

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.1)*W*Y + EPS

Est. Model Y= b1*X + b2*ETA + b3*X*ETA + b4*W*Y (GPP)

Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0

N = 20

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	1.00714	0.05647	0.82331	1.13552	0.99783	0.04662	0.91016	1.12712	0.99898	0.03428	0.90486	1.07936	1.00534	0.02504	0.94123	1.07827
	se(b1)	0.05214	0.00319	0.04601	0.0644	0.04181	0.00211	0.03735	0.05235	0.0361	0.00162	0.03291	0.04049	0.02514	0.00066	0.02379	0.02662
	b2	0.98737	0.17688	0.54265	1.61229	1.0151	0.15859	0.72237	1.73635	0.9775	0.10341	0.70185	1.26043	0.97962	0.0844	0.76704	1.19169
	se(b2)	0.14851	0.03159	0.06197	0.24027	0.11918	0.02372	0.07695	0.2189	0.10096	0.01603	0.07277	0.14227	0.0691	0.00733	0.05356	0.09477
	b3	1.00306	0.05387	0.87524	1.19028	1.00671	0.04419	0.89644	1.12363	1.00246	0.03311	0.90393	1.10776	0.999	0.02257	0.95626	1.05331
	se(b3)	0.05341	0.00931	0.03601	0.08423	0.0433	0.00649	0.02948	0.05742	0.03663	0.00434	0.02829	0.04736	0.02521	0.00252	0.0206	0.036
	b4	0.12067	0.13674	-0.2963	0.4746	0.09113	0.13001	-0.3609	0.33574	0.11491	0.09067	-0.1247	0.38	0.12146	0.07094	-0.0721	0.32905
	se(b4)	0.12014	0.02455	0.07482	0.19123	0.09858	0.01839	0.06348	0.15752	0.08519	0.01256	0.06591	0.11532	0.05767	0.00605	0.04533	0.07978
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	0.99944	0.05634	0.84867	1.15457	1.00133	0.04545	0.83942	1.12218	0.99998	0.03485	0.91811	1.06855	0.99151	0.02471	0.9256	1.04718
	se(b1)	0.05339	0.00282	0.04751	0.06187	0.04295	0.00201	0.03911	0.04911	0.03724	0.00161	0.03424	0.04145	0.02604	0.00069	0.02432	0.02739
	b2	1.01356	0.19028	0.65957	1.70778	1.00547	0.15383	0.58661	1.54948	0.97763	0.12336	0.67715	1.30812	0.96934	0.08762	0.81869	1.20781
	se(b2)	0.15149	0.03367	0.08611	0.2847	0.12135	0.02268	0.07176	0.17833	0.10235	0.0143	0.07324	0.14902	0.07171	0.00758	0.05747	0.09121
	b3	1.00684	0.05676	0.83258	1.11135	1.00136	0.04059	0.88886	1.08854	0.99905	0.03835	0.91493	1.08783	1.00034	0.03173	0.90186	1.06449
	se(b3)	0.05502	0.00934	0.0377	0.08155	0.04418	0.00524	0.03418	0.05597	0.03774	0.00465	0.02877	0.05424	0.02636	0.00211	0.02173	0.03417
	b4	0.08286	0.16362	-0.5921	0.35384	0.09913	0.13131	-0.3437	0.44741	0.121	0.1186	-0.2467	0.44567	0.12525	0.08301	-0.1303	0.28132
	se(b4)	0.1272	0.02885	0.0732	0.21665	0.10186	0.01804	0.06433	0.15731	0.08546	0.01224	0.05855	0.12205	0.0601	0.00634	0.04596	0.07723
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	0.99072	0.05323	0.84345	1.09987	0.99717	0.04016	0.89852	1.10302	0.9991	0.0373	0.919	1.10699	1.00198	0.02411	0.93958	1.0565
	se(b1)	0.05319	0.00331	0.04621	0.06192	0.04311	0.00197	0.03777	0.04856	0.03695	0.00158	0.03276	0.04344	0.02606	0.0007	0.02444	0.02806
	b2	1.05443	0.23601	0.64856	2.04102	1.02156	0.10436	0.83443	1.29102	1.0363	0.11907	0.77245	1.42713	1.01976	0.09124	0.82366	1.23554
	se(b2)	0.15145	0.03358	0.09234	0.27403	0.1189	0.01805	0.08514	0.17526	0.10497	0.01535	0.07073	0.14276	0.07085	0.00798	0.0506	0.09122
	b3	0.99153	0.05158	0.86632	1.12288	0.99544	0.04733	0.87188	1.10734	0.99933	0.03437	0.90989	1.06908	1.00011	0.02435	0.93857	1.07697
	se(b3)	0.05408	0.00878	0.03371	0.08218	0.04441	0.00658	0.03462	0.0622	0.03813	0.00506	0.02744	0.05061	0.02644	0.00255	0.0217	0.03467
	b4	-0.0544	0.22364	-1.1657	0.32632	-0.0174	0.10426	-0.2757	0.15518	-0.0287	0.11344	-0.3295	0.25666	-0.0216	0.09208	-0.2781	0.20183
	se(b4)	0.13995	0.03105	0.09313	0.26736	0.11043	0.0148	0.08456	0.16338	0.09765	0.01461	0.06875	0.13325	0.06586	0.00714	0.05132	0.08804

Table A5. OLS, N=30

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.5)*W*Y + EPS
Est. Model Y= b1*X + b2*ETA + b3*X*ETA
Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0
N = 30

True Weighting Matrix		T= 20 Mean	T= 20 STD	T= 20 Min	T= 20 Max	T= 30 Mean	T= 30 STD	T= 30 Min	T= 30 Max	T= 40 Mean	T= 40 STD	T= 40 Min	T= 40 Max	T= 80 Mean	T= 80 STD	T= 80 Min	T= 80 Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	1.01623	0.04521	0.90971	1.14688	1.01022	0.03899	0.9236	1.11183	1.01561	0.03415	0.92395	1.08941	1.01556	0.0225	0.96243	1.07068
	se(b1)	0.04868	0.00382	0.04171	0.06708	0.03863	0.0019	0.03541	0.046	0.03385	0.00155	0.03004	0.03848	0.02352	0.00074	0.02196	0.02515
	b2	1.99927	0.16591	1.63823	2.48541	1.99424	0.15148	1.61618	2.4528	2.01968	0.14811	1.72931	2.5158	2.00091	0.12568	1.66935	2.33269
	se(b2)	0.04972	0.00795	0.03568	0.07099	0.03984	0.00485	0.02734	0.05357	0.03334	0.00353	0.026	0.05019	0.02377	0.00164	0.01934	0.02769
	b3	1.02858	0.05449	0.88407	1.1561	1.0039	0.04688	0.89227	1.13527	1.01154	0.03791	0.91192	1.09703	1.01361	0.02754	0.94084	1.08579
	se(b3)	0.05135	0.00876	0.03432	0.07553	0.04067	0.00542	0.02917	0.06218	0.03394	0.00364	0.02609	0.04798	0.02399	0.00165	0.01979	0.02876
	b4																
	se(b4)																
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	1.03771	0.2171	-0.2797	2.0733	1.01406	0.53818	-3.439	2.74373	1.04607	0.20335	-0.4465	1.59918	0.96849	0.55864	-3.9435	1.47865
	se(b1)	0.20608	0.37457	0.08752	3.53526	0.20665	0.339	0.06583	2.46369	0.12699	0.09922	0.06063	0.81982	0.11647	0.36102	0.04242	3.63156
	b2	2.25655	6.74343	-25.899	61.6409	2.20809	6.19744	-50.931	19.8937	2.36771	1.44444	-1.8241	8.37013	1.52783	3.49419	-22.755	6.15139
	se(b2)	0.19446	0.33443	0.07478	3.20777	0.19957	0.31295	0.07111	2.35885	0.12875	0.10066	0.06252	0.75462	0.11432	0.34468	0.04168	3.47361
	b3	1.1311	0.76942	-0.0641	8.25744	1.00193	0.68372	-4.2401	3.24205	1.03704	0.2456	-0.3366	1.71478	0.89967	1.26453	-11.48	1.52815
	se(b3)	0.2032	0.32894	0.07141	3.12225	0.20483	0.32137	0.07521	2.43972	0.13075	0.10019	0.06314	0.76116	0.11512	0.34498	0.04193	3.47556
	b4																
	se(b4)																
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	1.04448	0.20116	0.72676	2.2377	1.03028	0.12306	0.81477	1.58018	1.02828	0.10411	0.84012	1.36306	1.02625	0.10045	0.84171	1.59104
	se(b1)	0.12524	0.04475	0.07266	0.41922	0.09711	0.04036	0.06504	0.39292	0.08036	0.01702	0.05509	0.13604	0.05714	0.01451	0.03967	0.12509
	b2	1.02613	0.29214	0.5249	2.25814	1.00936	0.30022	0.54716	2.29703	0.9997	0.26194	0.48552	1.87737	0.98055	0.23573	0.62131	1.82529
	se(b2)	0.12263	0.04031	0.07563	0.34882	0.09769	0.03781	0.05799	0.3409	0.08086	0.01875	0.04883	0.15033	0.05752	0.01496	0.03971	0.1183
	b3	1.02973	0.1917	0.64927	1.85782	1.03195	0.19086	0.74186	2.1336	1.02741	0.13444	0.75592	1.45494	1.02295	0.10576	0.81878	1.45584
	se(b3)	0.12781	0.04549	0.07822	0.42954	0.10097	0.04118	0.05922	0.3741	0.08239	0.01928	0.04881	0.14908	0.05794	0.01491	0.03915	0.1213
	b4																
	se(b4)																

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.1)*W*Y + EPS
Est. Model Y= b1*X + b2*ETA + b3*X*ETA
Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0
N = 30

True Weighting Matrix		T= 20 Mean	T= 20 STD	T= 20 Min	T= 20 Max	T= 30 Mean	T= 30 STD	T= 30 Min	T= 30 Max	T= 40 Mean	T= 40 STD	T= 40 Min	T= 40 Max	T= 80 Mean	T= 80 STD	T= 80 Min	T= 80 Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	1.00183	0.03893	0.91157	1.11009	0.99508	0.03253	0.9166	1.07575	0.9988	0.03	0.91153	1.07559	0.99961	0.01888	0.96036	1.04743
	se(b1)	0.0427	0.00276	0.03684	0.05337	0.03407	0.00135	0.03135	0.03953	0.02954	0.00098	0.0267	0.03189	0.02063	0.00048	0.0196	0.0221
	b2	1.11174	0.05125	0.98129	1.33468	1.1073	0.03975	1.00467	1.19298	1.11377	0.03551	1.01017	1.19084	1.11118	0.0282	1.04864	1.17892
	se(b2)	0.04373	0.00751	0.02974	0.06599	0.03519	0.00464	0.02357	0.04855	0.02915	0.00352	0.02224	0.0476	0.02086	0.0016	0.01655	0.0246
	b3	1.01104	0.0394	0.87604	1.12676	0.99272	0.03581	0.89246	1.08798	0.99778	0.0302	0.92234	1.07207	1.00041	0.01928	0.95661	1.05383
	se(b3)	0.04518	0.00826	0.0286	0.07198	0.03593	0.00509	0.02516	0.05343	0.02966	0.00357	0.02232	0.0455	0.02106	0.00161	0.01694	0.02547
	b4																
	se(b4)																
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	1.00535	0.04062	0.89442	1.09198	1.00048	0.03414	0.93023	1.12208	0.99737	0.03123	0.93567	1.07311	0.99974	0.02017	0.95951	1.0484
	se(b1)	0.04515	0.00325	0.04074	0.05999	0.03578	0.00173	0.03214	0.04088	0.03075	0.00138	0.02781	0.0371	0.02162	0.00053	0.02035	0.02368
	b2	1.11202	0.06334	0.9417	1.27123	1.11513	0.05821	0.96867	1.25037	1.11249	0.0498	0.99053	1.25526	1.11377	0.04001	1.024	1.19082
	se(b2)	0.04403	0.00736	0.03112	0.06976	0.03592	0.00429	0.02777	0.04995	0.03129	0.00355	0.02379	0.04148	0.02162	0.00178	0.01773	0.02859
	b3	1.00159	0.04622	0.90498	1.12885	1.00138	0.03662	0.90407	1.09424	1.00557	0.03213	0.9284	1.08636	0.99919	0.02196	0.94164	1.05188
	se(b3)	0.04651	0.00921	0.03177	0.07856	0.03661	0.00472	0.02816	0.05272	0.03184	0.00407	0.02381	0.04299	0.0218	0.00191	0.01665	0.02902
	b4																
	se(b4)																
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	0.99633	0.04455	0.87897	1.12869	0.99711	0.0337	0.91216	1.08556	1.00313	0.02806	0.93093	1.09692	1.00002	0.02074	0.94732	1.06118
	se(b1)	0.04445	0.0031	0.0383	0.05446	0.03592	0.00172	0.03301	0.04371	0.0308	0.00102	0.0288	0.03399	0.02156	0.00057	0.02053	0.02394
	b2	1.00053	0.04602	0.88259	1.11722	0.99791	0.04625	0.89303	1.13586	0.99674	0.04021	0.91613	1.09749	0.99105	0.03746	0.89131	1.09889
	se(b2)	0.04395	0.00624	0.03263	0.06312	0.03635	0.00405	0.02632	0.04714	0.03109	0.00395	0.0224	0.04284	0.02174	0.00193	0.01715	0.02923
	b3	0.98958	0.04242	0.88653	1.09651	0.99884	0.03826	0.88901	1.11661	1.00037	0.03015	0.8959	1.06607	0.99928	0.02193	0.9398	1.04426
	se(b3)	0.04578	0.00708	0.0318	0.06724	0.03748	0.00447	0.02681	0.04852	0.03168	0.00419	0.02311	0.04418	0.02192	0.00215	0.01712	0.03017
	b4																
	se(b4)																

Table A6. GPP, N=30

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.5)*W*Y + EPS
Est. Model Y= b1*X + b2*ETA + b3*X*ETA + b4*W*Y (GPP)
Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0
N = 30

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	0.9975	0.04355	0.90313	1.11204	0.99012	0.03502	0.90184	1.08444	0.99779	0.03343	0.90814	1.07794	0.99553	0.02011	0.95324	1.03859
	se(b1)	0.04618	0.00319	0.03993	0.05916	0.03677	0.00162	0.03325	0.04211	0.03209	0.00128	0.02887	0.03609	0.0223	0.00059	0.02082	0.02378
	b2	0.84783	0.14499	0.42368	1.29	0.85383	0.11563	0.55502	1.30163	0.83211	0.11207	0.58616	1.26281	0.84141	0.06705	0.67608	0.98203
	se(b2)	0.15809	0.03433	0.101	0.28827	0.12718	0.01981	0.07755	0.17085	0.10826	0.01228	0.0718	0.14643	0.07425	0.00776	0.06	0.09205
	b3	1.01158	0.04884	0.89109	1.13011	0.98774	0.04175	0.87415	1.07873	0.99566	0.03521	0.89708	1.06125	0.99637	0.02491	0.93178	1.06924
	se(b3)	0.04875	0.00823	0.03144	0.07465	0.0387	0.00509	0.02822	0.05693	0.03218	0.00349	0.02448	0.04686	0.02274	0.0016	0.01862	0.02733
	b4	0.57216	0.08112	0.36683	0.796	0.57002	0.06377	0.35	0.7033	0.5869	0.05953	0.36864	0.70523	0.57744	0.04086	0.46581	0.6769
	se(b4)	0.07571	0.01934	0.04581	0.15495	0.06106	0.01016	0.03501	0.08335	0.05147	0.00626	0.03376	0.06743	0.03537	0.00389	0.02713	0.04428
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	1.01353	0.15911	0.31097	1.29794	1.01311	0.38123	-1.5816	2.76867	1.02978	0.20771	-0.4473	1.73383	0.96165	0.56763	-4.3611	1.40486
	se(b1)	0.20241	0.35776	0.08665	3.3675	0.20315	0.32916	0.06597	2.34195	0.12505	0.09745	0.05989	0.8051	0.11561	0.36019	0.04215	3.6251
	b2	1.49728	1.74929	-6.5144	12.4658	1.79467	2.83913	-9.8127	19.3214	1.53048	1.97931	-1.7823	18.8166	0.96571	3.42002	-31.395	3.79669
	se(b2)	0.46976	0.72961	0.17145	6.85176	0.46323	0.663	0.14811	4.63088	0.28811	0.1998	0.11669	1.83295	0.2321	0.45329	0.08328	4.4871
	b3	1.11936	0.68527	-0.0365	7.37734	1.01346	0.44069	-0.996	2.63375	1.01991	0.23469	-0.3278	1.73085	0.8906	1.27695	-11.662	1.48686
	se(b3)	0.19949	0.31383	0.07117	2.97098	0.20173	0.31291	0.07486	2.33409	0.12878	0.09878	0.0629	0.76376	0.11424	0.34404	0.04162	3.46788
	b4	0.23625	0.41584	-0.9966	0.90434	0.26653	0.36362	-1.0346	0.88302	0.2994	0.62162	-4.4933	0.83114	0.27191	0.36358	-1.1127	0.84309
	se(b4)	0.16575	0.05098	0.06628	0.29183	0.13322	0.03625	0.05266	0.23633	0.11015	0.03966	0.0612	0.32932	0.08052	0.02059	0.03731	0.14637
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	1.0335	0.20238	0.70246	2.25819	1.01978	0.11965	0.81734	1.54643	1.021	0.10148	0.82563	1.3695	1.02103	0.09989	0.84114	1.58432
	se(b1)	0.12371	0.04235	0.07248	0.41816	0.09528	0.03303	0.06496	0.28855	0.07974	0.01657	0.05499	0.13375	0.05673	0.01442	0.03868	0.1251
	b2	1.68054	1.33093	0.29212	12.2686	1.57992	1.14074	0.33874	10.2341	1.46241	0.58008	0.44841	3.81289	1.48401	0.5379	0.60738	3.10737
	se(b2)	0.27673	0.0797	0.12232	0.60029	0.21447	0.06139	0.09198	0.42673	0.18138	0.04003	0.101	0.33437	0.12834	0.02818	0.0789	0.20332
	b3	1.01356	0.167	0.67926	1.56265	1.01138	0.1561	0.72011	1.74206	1.02014	0.13016	0.7555	1.41587	1.01689	0.10421	0.81796	1.44462
	se(b3)	0.12634	0.0435	0.07824	0.42976	0.09922	0.03497	0.05927	0.276	0.08181	0.01884	0.04885	0.1465	0.05752	0.01477	0.03923	0.12115
	b4	-0.7244	1.41848	-11.946	0.62901	-0.7281	1.60757	-13.653	0.58172	-0.5739	0.77016	-4.5856	0.63931	-0.6025	0.7249	-3.0728	0.50142
	se(b4)	0.24462	0.0761	0.10625	0.59587	0.19802	0.06421	0.09769	0.49191	0.16764	0.04307	0.08182	0.32022	0.12012	0.02755	0.06701	0.1957

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.1)*W*Y + EPS
Est. Model Y= b1*X + b2*ETA + b3*X*ETA + b4*W*Y (GPP)
Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0
N = 30

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	1.00084	0.03917	0.91282	1.11093	0.99432	0.03223	0.91625	1.07702	0.99854	0.03014	0.91157	1.07628	0.99904	0.01882	0.96035	1.04722
	se(b1)	0.04271	0.00276	0.03691	0.05304	0.03408	0.00134	0.0314	0.03937	0.02952	0.00098	0.0267	0.03191	0.02061	0.00048	0.01959	0.02207
	b2	0.99201	0.16266	0.60889	1.6142	0.99965	0.12901	0.6553	1.43016	0.97071	0.11811	0.67893	1.38707	0.9705	0.07086	0.79042	1.12395
	se(b2)	0.1456	0.03186	0.0903	0.2501	0.11769	0.01857	0.0717	0.15742	0.09976	0.0116	0.06728	0.13442	0.06855	0.00714	0.05498	0.0847
	b3	1.01026	0.03962	0.87994	1.12705	0.99235	0.03558	0.89233	1.09045	0.99785	0.03043	0.91777	1.07507	1.00013	0.01917	0.95709	1.05365
	se(b3)	0.04521	0.00825	0.0286	0.07219	0.03595	0.00508	0.02521	0.05321	0.02966	0.00358	0.02226	0.04551	0.02104	0.00161	0.01693	0.02548
	b4	0.1058	0.14583	-0.304	0.4692	0.09748	0.10876	-0.2397	0.36751	0.12827	0.09961	-0.2054	0.34172	0.12665	0.05787	-0.0027	0.27562
	se(b4)	0.12446	0.02916	0.07606	0.2274	0.10135	0.01555	0.05918	0.13492	0.08581	0.00974	0.06283	0.11716	0.05859	0.00587	0.04779	0.07156
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	1.00368	0.04101	0.88651	1.09675	1.00006	0.03445	0.9303	1.12247	0.99694	0.03123	0.93805	1.07271	0.99921	0.02033	0.95824	1.04857
	se(b1)	0.04517	0.00327	0.04077	0.06017	0.03578	0.00172	0.03205	0.04083	0.03074	0.00137	0.02785	0.0371	0.02161	0.00053	0.02035	0.02368
	b2	1.00061	0.19952	0.5977	1.71208	0.99361	0.12519	0.73887	1.38187	1.00047	0.11432	0.77878	1.41741	0.99451	0.09207	0.80373	1.28326
	se(b2)	0.15376	0.03315	0.09738	0.2643	0.12237	0.01918	0.07419	0.17918	0.10347	0.01584	0.06271	0.14136	0.07237	0.0092	0.05591	0.10411
	b3	1.0014	0.04663	0.90089	1.12149	1.00136	0.03711	0.90235	1.09568	1.00506	0.03248	0.92766	1.08652	0.99879	0.02199	0.94071	1.05333
	se(b3)	0.04653	0.00923	0.03177	0.0787	0.03663	0.00471	0.02821	0.05265	0.03184	0.00406	0.02376	0.04298	0.02179	0.00191	0.01666	0.02902
	b4	0.09742	0.1832	-0.4934	0.48665	0.10766	0.11067	-0.2428	0.36367	0.10048	0.10745	-0.3471	0.29781	0.10614	0.09067	-0.1746	0.26124
	se(b4)	0.13249	0.03068	0.07947	0.22939	0.10443	0.0164	0.07382	0.15479	0.08911	0.01383	0.05821	0.13098	0.06204	0.00789	0.04781	0.0908
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	0.99541	0.04453	0.87496	1.12858	0.99611	0.03355	0.91221	1.08449	1.00269	0.02816	0.93285	1.09677	0.99973	0.02093	0.94739	1.06215
	se(b1)	0.04449	0.00307	0.03837	0.05402	0.03594	0.00172	0.03304	0.04373	0.03081	0.00102	0.02881	0.034	0.02156	0.00056	0.02054	0.02394
	b2	1.07871	0.19182	0.73269	1.68298	1.05274	0.1639	0.6604	1.72744	1.02887	0.1249	0.73914	1.47376	1.03207	0.08617	0.84352	1.23196
	se(b2)	0.15378	0.03117	0.09976	0.23951	0.12367	0.02073	0.08004	0.18729	0.10214	0.01494	0.07292	0.14182	0.0716	0.00775	0.05553	0.09106
	b3	0.98846	0.04246	0.87597	1.08691	0.99767	0.03757	0.88898	1.11261	0.9998	0.03009	0.89622	1.06451	0.9989	0.02179	0.93907	1.04495
	se(b3)	0.04585	0.00708	0.0319	0.06755	0.03753	0.00447	0.02672	0.04862	0.03171	0.00418	0.02317	0.04417	0.02193	0.00214	0.01716	0.03014
	b4	-0.0762	0.18217	-0.6172	0.26066	-0.0576	0.16572	-0.6766	0.35701	-0.0351	0.1322	-0.4601	0.25559	-0.043	0.09685	-0.3026	0.13288
	se(b4)	0.14513	0.03103	0.08718	0.23783	0.11886	0.02068	0.07555	0.1835	0.09716	0.01462	0.07002	0.13798	0.06898	0.008	0.05323	0.09245

Table A7. OLS, N=40

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.5)*W*Y + EPS
Est. Model Y= b1*X + b2*ETA + b3*X*ETA
Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0
N = 40

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	1.01699	0.03823	0.92247	1.1087	1.01164	0.03399	0.93884	1.14823	1.0108	0.02741	0.91869	1.08718	1.00967	0.01859	0.95693	1.0561
	se(b1)	0.04233	0.00253	0.03698	0.05002	0.03411	0.00169	0.03073	0.03849	0.02931	0.00125	0.027	0.0335	0.02056	0.00063	0.01908	0.02209
	b2	2.01308	0.15633	1.70162	2.72871	1.99871	0.15865	1.64456	2.47042	2.01102	0.13205	1.743	2.35401	2.01063	0.12679	1.58763	2.27215
	se(b2)	0.04317	0.00693	0.03048	0.07336	0.03407	0.00387	0.02685	0.04178	0.02924	0.00269	0.02335	0.03622	0.02071	0.00139	0.01774	0.02402
	b3	1.00915	0.04851	0.89834	1.12525	1.00688	0.04191	0.85707	1.08922	1.01061	0.033	0.93238	1.09311	1.01382	0.02685	0.95305	1.08127
	se(b3)	0.04458	0.00726	0.0312	0.07262	0.03465	0.00426	0.0268	0.04547	0.0297	0.00273	0.02437	0.03728	0.02078	0.00143	0.01717	0.02388
	b4																
	se(b4)																
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	0.53205	3.82978	-35.904	3.03654	0.86906	1.92856	-15.066	9.11769	1.05775	1.13351	-4.7828	9.91887	1.18463	0.99741	-1.3366	6.69938
	se(b1)	1.26761	6.32506	0.08949	54.9605	0.456	1.37871	0.06915	10.4814	0.28908	0.5906	0.06859	4.68305	0.21657	0.33598	0.04831	1.6635
	b2	-12.082	103.486	-953.33	19.6005	1.61063	23.92	-140.12	173.674	2.74397	14.5704	-58.204	128.757	2.60605	6.11758	-14.429	40.6184
	se(b2)	1.22985	6.2353	0.09054	56.9404	0.44623	1.2973	0.07742	9.54934	0.29166	0.58181	0.06662	4.21668	0.21431	0.32581	0.05141	1.53851
	b3	1.3391	5.78592	-30.183	47.2579	0.93445	2.06072	-12.715	12.8039	0.93127	1.05461	-7.8533	3.17674	1.11317	0.95772	-2.382	6.63895
	se(b3)	1.27753	6.30868	0.0917	55.2214	0.46862	1.40267	0.07905	9.59533	0.29286	0.57443	0.06472	4.10282	0.2161	0.33128	0.05123	1.61681
	b4																
	se(b4)																
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	1.07173	0.39643	-1.2589	2.69065	0.86876	2.10826	-16.429	8.92597	0.37944	5.9364	-55.897	8.39255	1.1268	0.61604	-0.6051	6.56386
	se(b1)	0.20341	0.18269	0.08014	1.57024	0.30105	0.75427	0.07348	5.76186	0.48659	2.24599	0.0611	19.7427	0.12969	0.22315	0.04572	1.87193
	b2	0.97461	0.88419	-6.9599	2.58106	0.94531	0.90345	-5.517	3.31833	0.78555	1.58818	-10.235	2.35085	1.02468	0.55616	-1.6761	3.03104
	se(b2)	0.20227	0.16096	0.07464	1.31112	0.28708	0.68273	0.06872	5.57161	0.46383	2.11941	0.0618	18.7901	0.12627	0.20685	0.0453	1.72165
	b3	1.05322	0.43262	-1.5282	2.55389	0.99103	1.62506	-12.18	8.17588	0.42747	3.50588	-28.118	1.68919	1.0702	0.48679	-1.8901	3.50598
	se(b3)	0.20712	0.16323	0.07579	1.33001	0.29242	0.68514	0.06986	5.46102	0.46644	2.106	0.06273	18.5324	0.12622	0.20278	0.04607	1.6666
	b4																
	se(b4)																

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.1)*W*Y + EPS
Est. Model Y= b1*X + b2*ETA + b3*X*ETA
Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0
N = 40

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	1.00346	0.0329	0.92412	1.07181	0.99797	0.02596	0.93628	1.07225	0.99931	0.02472	0.93888	1.05041	0.99705	0.01636	0.93891	1.03403
	se(b1)	0.03681	0.0017	0.03313	0.04225	0.02958	0.00109	0.02771	0.03236	0.02538	0.00086	0.02339	0.02785	0.01782	0.00036	0.01704	0.01872
	b2	1.11298	0.04186	1.03759	1.25517	1.10979	0.03738	1.01193	1.195	1.10895	0.02842	1.04621	1.17869	1.11528	0.01935	1.05912	1.16114
	se(b2)	0.03771	0.00696	0.02431	0.0682	0.02962	0.0038	0.02185	0.03806	0.02535	0.00262	0.01941	0.03241	0.01797	0.00135	0.01535	0.02129
	b3	0.99788	0.04029	0.88775	1.08239	0.99705	0.03012	0.8844	1.05454	0.99802	0.02683	0.93325	1.06806	1.00066	0.01982	0.94972	1.04349
	se(b3)	0.03896	0.00733	0.02473	0.06751	0.03012	0.00413	0.02252	0.04142	0.02574	0.00265	0.02078	0.03294	0.01803	0.0014	0.01442	0.02117
	b4																
	se(b4)																
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	0.99413	0.03599	0.892	1.10048	0.99584	0.03243	0.9171	1.08298	0.99628	0.0241	0.9397	1.06324	0.99947	0.02003	0.94493	1.04214
	se(b1)	0.03886	0.00198	0.03429	0.0451	0.03139	0.0016	0.02908	0.03862	0.02701	0.00089	0.02486	0.02983	0.01903	0.00045	0.01811	0.02058
	b2	1.12346	0.05341	1.02015	1.27851	1.10148	0.04974	1.00773	1.21277	1.10306	0.05186	0.99383	1.22921	1.11292	0.04394	1.01439	1.22473
	se(b2)	0.03897	0.00504	0.02697	0.05357	0.03176	0.00403	0.0243	0.04636	0.0276	0.00277	0.02155	0.03431	0.019	0.00128	0.01604	0.02212
	b3	1.00366	0.04167	0.90809	1.12227	0.9957	0.03539	0.88686	1.13488	1.00303	0.02812	0.93135	1.05333	1.00011	0.02025	0.95878	1.04979
	se(b3)	0.04034	0.00592	0.02723	0.06244	0.03237	0.00435	0.02432	0.04608	0.02796	0.00289	0.02169	0.03472	0.01919	0.00145	0.01623	0.02285
	b4																
	se(b4)																
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	0.99939	0.04093	0.90835	1.14449	1.00089	0.03324	0.91786	1.07805	1.00083	0.02855	0.92057	1.06999	1.00111	0.02025	0.95634	1.05025
	se(b1)	0.03875	0.00204	0.03477	0.04624	0.03129	0.00123	0.02862	0.03529	0.027	0.00095	0.025	0.03068	0.01895	0.00034	0.01822	0.0198
	b2	0.99515	0.04295	0.89825	1.10207	1.00252	0.04209	0.89794	1.10918	0.99795	0.03855	0.87155	1.08833	0.99662	0.02881	0.93685	1.07567
	se(b2)	0.03958	0.00594	0.0289	0.05815	0.03134	0.00386	0.02383	0.04318	0.02705	0.00254	0.02162	0.03581	0.01886	0.00149	0.01626	0.02329
	b3	0.99987	0.03864	0.9117	1.10403	1.00432	0.03622	0.92679	1.09067	0.99942	0.03055	0.92259	1.07412	1.00375	0.02207	0.93996	1.06113
	se(b3)	0.04063	0.00649	0.02906	0.06056	0.03206	0.00406	0.02419	0.04454	0.02746	0.00256	0.02156	0.03695	0.01895	0.00161	0.01589	0.02365
	b4																
	se(b4)																

Table A8. GPP, N=40

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.5)*W*Y + EPS
Est. Model Y= b1*X + b2*ETA + b3*X*ETA + b4*W*Y (GPP)
Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0
N = 40

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	1.00261	0.03626	0.9222	1.07855	0.99871	0.03008	0.9291	1.08626	0.99641	0.02521	0.9199	1.06646	0.99606	0.01791	0.94103	1.03872
	se(b1)	0.0408	0.0022	0.03664	0.04857	0.03288	0.0015	0.02994	0.03689	0.0282	0.00114	0.02584	0.03252	0.01975	0.00052	0.01839	0.02088
	b2	0.86152	0.16405	0.5831	1.49163	0.83992	0.10645	0.55561	1.14288	0.85118	0.1021	0.63748	1.05661	0.84604	0.06987	0.71545	1.03817
	se(b2)	0.16188	0.03385	0.09414	0.29608	0.12998	0.02236	0.07832	0.18203	0.1081	0.01586	0.069	0.15175	0.07483	0.008	0.0594	0.09463
	b3	0.99491	0.04838	0.84155	1.10909	0.99594	0.03935	0.84791	1.07443	0.99783	0.03168	0.92722	1.08971	0.99946	0.02456	0.94155	1.05062
	se(b3)	0.04302	0.00711	0.03034	0.07193	0.03342	0.00418	0.02611	0.04466	0.02856	0.00259	0.02352	0.03581	0.01997	0.00137	0.01658	0.02303
	b4	0.56905	0.08431	0.2197	0.72716	0.57567	0.06017	0.40982	0.69631	0.5755	0.06032	0.451	0.70941	0.57721	0.04286	0.47334	0.665
	se(b4)	0.07793	0.01704	0.04485	0.14994	0.06289	0.01164	0.03855	0.09171	0.05196	0.00778	0.03365	0.07423	0.03593	0.00424	0.02711	0.04769
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	0.71059	2.61755	-23.68	2.99587	0.88654	1.606	-13.2	6.57052	1.02731	0.82354	-4.6599	5.56885	1.15095	0.92689	-1.3268	6.46105
	se(b1)	1.25082	6.23293	0.08946	53.8653	0.44934	1.36788	0.06897	10.3927	0.27578	0.56546	0.06824	4.57489	0.21152	0.3306	0.04758	1.65475
	b2	-3.1414	38.7294	-272.49	49.161	2.43716	11.5812	-60.622	84.9191	2.37559	4.75588	-8.3457	31.0126	2.30216	4.99498	-11.681	39.961
	se(b2)	2.85241	14.8143	0.15451	127.935	0.94554	3.07684	0.15577	24.1432	0.54248	1.19069	0.128	10.8978	0.35951	0.50549	0.07099	3.18315
	b3	1.48	6.80183	-28.629	60.2255	0.97293	2.14784	-14.079	14.0446	0.93496	1.24015	-10.325	3.21476	1.10249	0.90174	-2.0336	6.36992
	se(b3)	1.25928	6.21214	0.09177	54.1255	0.46151	1.39076	0.07851	9.54193	0.2799	0.54767	0.06463	3.99685	0.21105	0.32598	0.0506	1.60802
	b4	-0.0845	1.46632	-12.078	0.88698	-0.3378	2.62471	-24.333	0.89932	-0.3093	3.56549	-30.002	0.86563	-0.2354	2.05331	-15.745	0.92477
	se(b4)	0.19731	0.08908	0.07162	0.66555	0.17101	0.07498	0.05536	0.55703	0.13222	0.06574	0.05368	0.49639	0.09755	0.05628	0.03061	0.34654
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	1.0499	0.39378	-1.3005	2.79908	0.8318	1.85	-14.949	4.62853	0.91775	1.70292	-13.622	8.67368	1.0933	0.6159	-0.6032	6.34883
	se(b1)	0.19908	0.17897	0.07943	1.57034	0.28012	0.68005	0.07312	5.62387	0.34554	1.2574	0.06101	8.38703	0.12258	0.20276	0.04553	1.8343
	b2	2.25925	2.47457	-8.9403	16.5195	2.10121	3.77444	-19.178	27.7485	-0.6755	25.1191	-247.16	24.4897	1.9776	2.37922	-5.8953	18.0066
	se(b2)	0.37847	0.22873	0.16106	2.16417	0.41085	0.63525	0.14979	5.70591	0.44589	1.17727	0.09397	7.94141	0.19501	0.19919	0.07858	1.72591
	b3	1.03689	0.42395	-1.452	2.56717	0.93937	1.44112	-11.654	4.37885	0.85598	2.47723	-13.895	14.7568	1.06096	0.46652	-1.8665	3.21668
	se(b3)	0.20269	0.15939	0.07506	1.32976	0.27382	0.63072	0.06948	5.32768	0.33401	1.17714	0.06205	7.87476	0.11943	0.18342	0.04586	1.6332
	b4	-1.5079	2.64861	-20.049	0.62907	-1.6873	3.71796	-25.289	0.70201	-1.3999	4.12104	-35.531	0.66982	-1.391	3.51683	-24.703	0.55559
	se(b4)	0.29836	0.11427	0.13308	0.70584	0.24156	0.09503	0.09771	0.55818	0.19308	0.06906	0.08589	0.49053	0.13893	0.05525	0.06586	0.35043

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.1)*W*Y + EPS
Est. Model Y= b1*X + b2*ETA + b3*X*ETA + b4*W*Y (GPP)
Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0
N = 40

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	1.00276	0.0327	0.92493	1.07281	0.99768	0.02588	0.93617	1.07187	0.99896	0.02493	0.93687	1.05387	0.9967	0.01633	0.93848	1.03444
	se(b1)	0.03681	0.00171	0.03308	0.04237	0.02958	0.0011	0.02761	0.03235	0.02537	0.00086	0.0234	0.02785	0.01781	0.00036	0.01704	0.01871
	b2	1.01131	0.19372	0.70869	1.7073	0.98332	0.1118	0.6871	1.25136	0.98497	0.10987	0.75647	1.28983	0.97374	0.07883	0.83661	1.20411
	se(b2)	0.14723	0.03034	0.08342	0.24908	0.11808	0.02097	0.06989	0.16845	0.09789	0.01426	0.06274	0.13775	0.06803	0.00717	0.05456	0.08764
	b3	0.99725	0.04068	0.88669	1.08098	0.99687	0.03018	0.8844	1.05212	0.99792	0.0268	0.93331	1.06998	1.00024	0.01968	0.94959	1.04151
	se(b3)	0.03898	0.00733	0.02482	0.06746	0.03014	0.00415	0.02253	0.04148	0.02574	0.00265	0.0208	0.03294	0.01802	0.0014	0.01441	0.02117
	b4	0.08909	0.17001	-0.5752	0.36466	0.11313	0.10049	-0.143	0.38083	0.11205	0.10012	-0.1797	0.33998	0.12664	0.06796	-0.0626	0.24088
	se(b4)	0.12776	0.0262	0.07171	0.2224	0.10215	0.01813	0.06301	0.1443	0.08522	0.01206	0.05618	0.11933	0.05872	0.00631	0.04726	0.07473
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	0.99382	0.03586	0.89262	1.10042	0.99533	0.03236	0.91499	1.08283	0.99578	0.02438	0.93867	1.06488	0.99906	0.01996	0.94491	1.04124
	se(b1)	0.03889	0.00199	0.03433	0.04511	0.0314	0.0016	0.0291	0.03867	0.027	0.00088	0.02484	0.02984	0.01903	0.00045	0.01811	0.02053
	b2	1.05165	0.18741	0.7013	1.84647	0.99609	0.1259	0.71425	1.36577	1.00459	0.12969	0.71036	1.41024	1.00528	0.07875	0.82281	1.19793
	se(b2)	0.15664	0.03289	0.09939	0.26974	0.12278	0.01992	0.08664	0.18034	0.10475	0.01588	0.05855	0.14179	0.07242	0.00797	0.05739	0.09966
	b3	1.00331	0.04149	0.90828	1.12183	0.9955	0.03564	0.88674	1.13464	1.00258	0.02823	0.9313	1.05234	0.99993	0.02013	0.95919	1.05021
	se(b3)	0.04039	0.00592	0.02718	0.06249	0.03239	0.00434	0.02427	0.04606	0.02797	0.00289	0.02172	0.03468	0.01918	0.00145	0.01622	0.02283
	b4	0.06325	0.16316	-0.6031	0.33916	0.09396	0.11524	-0.2515	0.32338	0.0879	0.12401	-0.2773	0.39463	0.09543	0.08092	-0.1198	0.27885
	se(b4)	0.13573	0.02797	0.0891	0.23579	0.10759	0.01861	0.07427	0.1697	0.09211	0.01424	0.05312	0.13118	0.06294	0.00737	0.04897	0.08606
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	0.99847	0.04097	0.90774	1.14393	1.00032	0.03349	0.91769	1.07771	1.00028	0.02848	0.91872	1.07016	1.00093	0.02027	0.95562	1.04968
	se(b1)	0.03876	0.00205	0.03477	0.04629	0.0313	0.00123	0.02864	0.0353	0.02701	0.00095	0.02492	0.03069	0.01896	0.00033	0.01822	0.0198
	b2	1.08264	0.22923	0.69045	1.74534	1.07135	0.17533	0.77721	1.73824	1.05063	0.14766	0.79521	1.68368	1.02151	0.07995	0.84112	1.22012
	se(b2)	0.15259	0.03214	0.09854	0.2664	0.12145	0.02095	0.08708	0.20654	0.1029	0.01757	0.05864	0.16565	0.06985	0.0067	0.05386	0.08624
	b3	0.99865	0.03894	0.91358	1.10548	1.00355	0.03603	0.9268	1.08678	0.99871	0.03108	0.9153	1.07502	1.00358	0.02197	0.94005	1.06117
	se(b3)	0.04066	0.0065	0.0291	0.0604	0.03209	0.00407	0.02417	0.04458	0.02747	0.00256	0.02162	0.03697	0.01896	0.00161	0.0159	0.02365
	b4	-0.0879	0.22476	-0.7307	0.30771	-0.0697	0.17884	-0.7389	0.24081	-0.0533	0.14639	-0.5852	0.20707	-0.0262	0.08631	-0.2275	0.15787
	se(b4)	0.14785	0.03064	0.09019	0.25147	0.11713	0.02183	0.08649	0.20148	0.09921	0.01737	0.06018	0.1556	0.06818	0.00713	0.05252	0.08616

Table A9. OLS, N=50

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.5)*W*Y + EPS
Est. Model Y= b1*X + b2*ETA + b3*X*ETA
Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0
N = 50

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	1.00806	0.03936	0.87626	1.09815	1.00444	0.0316	0.91523	1.08471	1.00988	0.02728	0.95437	1.08374	1.00764	0.02131	0.94968	1.05453
	se(b1)	0.03791	0.00301	0.033	0.05062	0.03072	0.00152	0.02763	0.03549	0.02655	0.00111	0.02451	0.02975	0.01867	0.00057	0.01745	0.02046
	b2	1.98983	0.15577	1.71531	2.68082	2.00678	0.14033	1.70375	2.37473	2.01972	0.14856	1.69583	2.52359	2.00672	0.12932	1.7383	2.48693
	se(b2)	0.03871	0.00563	0.0301	0.05913	0.03126	0.00344	0.02396	0.04341	0.02689	0.0024	0.02127	0.03196	0.01856	0.00127	0.01617	0.02449
	b3	1.01048	0.0422	0.92115	1.14124	1.00395	0.03121	0.94189	1.07724	1.00984	0.03379	0.91508	1.09625	1.00512	0.02085	0.95402	1.05751
	se(b3)	0.03985	0.00639	0.03128	0.06768	0.03178	0.00365	0.02277	0.04323	0.02714	0.00271	0.02081	0.03396	0.0187	0.00128	0.01643	0.0245
	b4																
	se(b4)																
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	1.23672	2.38422	-5.5178	16.8339	0.58532	3.65525	-34.066	5.09493	1.23303	2.00527	-2.7443	19.7007	1.23696	3.14543	-6.5125	30.8623
	se(b1)	0.98934	2.51379	0.10306	20.8161	0.59511	1.74767	0.08462	16.5326	0.54607	1.63464	0.07336	16.2375	0.4886	1.88771	0.05699	18.5525
	b2	1.24251	10.1084	-61.516	66.5856	1.88167	5.34362	-21.919	34.289	-0.9976	32.4366	-319.77	29.3264	1.74551	10.4352	-77.795	39.6268
	se(b2)	0.99456	2.60218	0.10756	21.355	0.62603	2.01449	0.08579	19.4772	0.53561	1.56177	0.07595	15.4757	0.50256	2.0094	0.05837	19.7784
	b3	1.24758	2.55173	-15.4	12.9972	0.46302	5.15664	-47.951	12.8124	1.21746	1.61785	-3.3014	13.3653	1.39326	5.46236	-11.044	53.6221
	se(b3)	1.00348	2.57861	0.11319	21.0805	0.64809	2.15319	0.08863	20.9439	0.53774	1.53943	0.08002	15.2473	0.50332	1.9745	0.06098	19.3912
	b4																
	se(b4)																
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	0.96169	0.58521	-1.345	3.21945	0.99292	3.54851	-12.683	32.1108	0.87366	1.23553	-7.9753	5.70068	0.86367	1.26133	-7.5837	4.21695
	se(b1)	0.41706	0.51949	0.11465	4.24182	0.99998	3.15969	0.08246	23.1908	0.52328	2.05509	0.06431	20.3259	0.28396	0.47149	0.05214	3.04907
	b2	1.05702	1.56042	-5.1494	10.9218	0.12307	7.57844	-67.243	14.7325	-0.7632	17.3114	-171.99	4.09477	0.79124	2.4693	-9.4954	16.0022
	se(b2)	0.41609	0.56705	0.08789	5.00302	0.98794	3.11933	0.08555	22.0038	0.51617	2.03492	0.06183	20.1384	0.28432	0.47839	0.04978	2.99031
	b3	1.04858	0.87416	-0.1363	7.19456	0.46281	3.54534	-31.751	4.86675	1.2886	4.26678	-2.2517	43.0542	0.78625	1.29236	-6.6608	4.35675
	se(b3)	0.42582	0.57284	0.09041	5.07438	1.00417	3.14209	0.08249	21.8158	0.52511	2.05789	0.06295	20.3425	0.28344	0.47462	0.05014	2.97563
	b4																
	se(b4)																

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.1)*W*Y + EPS
Est. Model Y= b1*X + b2*ETA + b3*X*ETA
Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0
N = 50

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	1.00123	0.0334	0.89836	1.07205	0.99514	0.02762	0.91435	1.05254	1.00139	0.02255	0.94898	1.05723	0.99807	0.01751	0.95369	1.04306
	se(b1)	0.03258	0.00224	0.02873	0.04328	0.02636	0.00104	0.02429	0.0295	0.0227	0.00069	0.02142	0.02593	0.01595	0.00028	0.01526	0.01689
	b2	1.10878	0.03985	0.99405	1.2091	1.11034	0.0294	1.03172	1.17334	1.1136	0.03021	1.02956	1.17185	1.11122	0.01782	1.05738	1.14471
	se(b2)	0.03339	0.0055	0.02392	0.05273	0.02689	0.00349	0.01855	0.03773	0.02303	0.00234	0.01771	0.02778	0.01587	0.0012	0.01375	0.02123
	b3	1.00204	0.03243	0.928	1.10939	0.99522	0.02469	0.92555	1.04487	1.00252	0.02249	0.94517	1.05338	0.99823	0.01601	0.96146	1.03663
	se(b3)	0.03437	0.0061	0.02409	0.05646	0.02734	0.00365	0.01763	0.03887	0.02325	0.00262	0.01752	0.02974	0.01599	0.00121	0.01352	0.02124
	b4																
	se(b4)																
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	1.00175	0.03692	0.90954	1.10304	1.00098	0.03	0.92224	1.06963	0.99645	0.02553	0.90812	1.06043	0.99815	0.01932	0.94951	1.04792
	se(b1)	0.0353	0.00199	0.03138	0.04592	0.02861	0.00113	0.0262	0.03299	0.02459	0.00074	0.02304	0.02759	0.01726	0.00034	0.01644	0.01799
	b2	1.10932	0.05548	0.9743	1.25038	1.11123	0.04511	0.98536	1.21408	1.10858	0.04893	0.9718	1.21952	1.11231	0.04166	1.02454	1.24992
	se(b2)	0.0349	0.00562	0.02462	0.05274	0.02905	0.00389	0.02205	0.04869	0.02477	0.0028	0.01945	0.03279	0.01716	0.00118	0.01503	0.02243
	b3	1.00539	0.03955	0.91187	1.1303	1.00253	0.02963	0.93241	1.07719	1.00499	0.02454	0.93748	1.07456	0.99666	0.01784	0.95206	1.04461
	se(b3)	0.03595	0.00598	0.0242	0.05451	0.02973	0.00406	0.02212	0.04933	0.02512	0.00294	0.01928	0.03431	0.01729	0.00119	0.01477	0.02244
	b4																
	se(b4)																
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	1.00682	0.03597	0.90615	1.07177	0.99781	0.02914	0.9394	1.07954	0.99522	0.02385	0.92167	1.04582	1.00157	0.0166	0.96139	1.04021
	se(b1)	0.03524	0.00206	0.03159	0.04212	0.02833	0.00099	0.02623	0.03154	0.02454	0.00069	0.02285	0.02676	0.01722	0.00031	0.01646	0.01807
	b2	0.99702	0.04074	0.88634	1.09947	1.00251	0.03845	0.89771	1.11306	1.00193	0.04085	0.9157	1.11081	0.99441	0.03209	0.92125	1.06567
	se(b2)	0.03501	0.00505	0.02518	0.04817	0.02851	0.00332	0.02237	0.03702	0.02463	0.0028	0.01915	0.03199	0.01735	0.00134	0.01437	0.02174
	b3	0.99859	0.03563	0.91808	1.09301	1.00055	0.02935	0.91516	1.07362	0.99643	0.0271	0.93035	1.05924	0.99854	0.01749	0.95884	1.04052
	se(b3)	0.03598	0.0055	0.02466	0.05009	0.02905	0.00341	0.02237	0.03747	0.02511	0.00301	0.0194	0.03296	0.01755	0.00147	0.01401	0.0224
	b4																
	se(b4)																

Table A10. GPP, N=50

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.5)*W*Y + EPS

Est. Model Y= b1*X + b2*ETA + b3*X*ETA + b4*W*Y (GPP)

Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0

N = 50

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	0.99729	0.03798	0.88182	1.08386	0.99369	0.03112	0.90703	1.06599	0.99868	0.02451	0.94579	1.07222	0.99673	0.02003	0.94795	1.04686
	se(b1)	0.03692	0.00283	0.03237	0.04965	0.02989	0.0014	0.02734	0.03409	0.02578	0.00102	0.02395	0.02891	0.01811	0.00051	0.01704	0.01963
	b2	0.88225	0.1693	0.53207	1.33189	0.86347	0.12324	0.54084	1.2236	0.84368	0.1093	0.59498	1.19762	0.84863	0.06337	0.68366	0.96821
	se(b2)	0.16555	0.03524	0.0819	0.26786	0.13153	0.02035	0.08851	0.18639	0.11224	0.01744	0.07081	0.19163	0.07596	0.00796	0.05646	0.09281
	b3	1.00138	0.04155	0.91643	1.13041	0.9941	0.031	0.9287	1.07025	1.00091	0.03089	0.91913	1.07888	0.99382	0.01969	0.94931	1.04423
	se(b3)	0.03882	0.00624	0.02902	0.06632	0.03093	0.00355	0.02252	0.04238	0.02635	0.00258	0.02045	0.03286	0.01814	0.00118	0.01589	0.02321
	b4	0.55366	0.08989	0.32925	0.72678	0.56709	0.06967	0.29793	0.73305	0.58053	0.05926	0.42403	0.74114	0.57626	0.04082	0.45436	0.69235
	se(b4)	0.08108	0.01805	0.03868	0.15009	0.06375	0.01031	4.56E-02	0.09491	0.05409	0.00833	0.03645	0.08234	0.0369	0.00424	0.02948	0.05019
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	1.3136	2.19319	-1.7727	16.9686	0.54897	3.6055	-33.853	5.0293	1.3356	3.05715	-3.3873	30.736	1.23746	3.01753	-6.609	29.3962
	se(b1)	0.86045	2.19334	0.10305	20.6147	0.57951	1.73824	0.0847	16.5476	0.51697	1.54736	0.07308	15.409	0.48149	1.88071	0.057	18.5106
	b2	4.51709	17.0236	-11.597	154.576	3.84317	17.429	-41.882	151.04	5.33806	13.3342	-42.903	82.4301	1.36331	15.6694	-127.33	68.0666
	se(b2)	1.17263	2.51494	0.18655	22.9705	0.90326	2.2631	0.1176	20.5343	0.83634	2.38512	0.12969	23.5281	0.68292	2.33822	0.06723	22.5778
	b3	1.38629	1.87367	-1.4682	13.3242	0.45043	5.12334	-47.66	13.0807	1.25495	2.10606	-3.1996	20.3366	1.3919	5.18195	-10.391	50.9304
	se(b3)	0.86772	2.21928	0.11319	20.8737	0.63373	2.14892	0.08869	20.965	0.50791	1.45384	0.08013	14.4604	0.49584	1.96733	0.06098	19.3536
	b4	-1.4163	5.69928	-48.147	0.91712	-0.6667	3.60923	-32.553	0.91175	-1.8684	4.92446	-27.405	0.90648	-0.7556	2.69471	-18.916	0.91601
	se(b4)	0.24697	0.14446	0.06317	0.77954	0.18596	0.09703	0.05056	0.60794	0.19561	0.12913	0.04887	0.55411	0.12113	0.06537	0.03233	0.38619
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	0.98395	0.54563	-0.9502	3.36792	0.826	2.24605	-12.805	16.5407	0.82702	1.14866	-7.9628	4.26344	0.87044	1.1814	-7.0356	3.99956
	se(b1)	0.40339	0.50492	0.11483	4.23679	0.80507	2.53208	0.08249	21.7537	0.49497	2.02801	0.06432	20.1134	0.26265	0.44297	0.05208	3.04654
	b2	3.48224	6.24744	-6.176	45.3437	7.26985	39.1171	-33.789	381.702	3.7092	9.9709	-64.178	41.2797	3.25261	8.63244	-15.452	53.7769
	se(b2)	0.6012	0.65214	0.18117	5.8213	0.98216	2.62605	0.14536	21.0607	0.67327	2.57574	0.11378	25.7856	0.35443	0.48554	0.07355	3.15342
	b3	1.05156	0.87416	-0.3005	7.35583	0.46894	2.43627	-15.679	3.49971	1.30691	4.19322	-0.813	42.5357	0.80416	1.22503	-6.1141	4.19484
	se(b3)	0.41274	0.56126	0.09017	5.06821	0.80186	2.45488	0.08165	20.5138	0.49694	2.03147	0.06297	20.13	0.26329	0.45021	0.0501	2.97317
	b4	-2.2973	3.80009	-26.504	0.72134	-3.404	7.11306	-47.82	0.88853	-3.8243	6.595	-32.505	0.67071	-2.8238	6.72506	-43.168	0.72915
	se(b4)	0.33815	0.14746	0.11396	0.78755	0.28255	0.13775	0.062	0.64643	0.26206	0.13226	0.09002	0.55838	0.16171	0.07701	0.05715	0.39277

True Model Y= beta1(1.0)*X + beta2(1.0)*ETA + beta3(1.0)*X*ETA + rho(0.1)*W*Y + EPS

Est. Model Y= b1*X + b2*ETA + b3*X*ETA + b4*W*Y (GPP)

Est. Matrix Wij = 1/(N-1), i <> j; otherwise Wij = 0

N = 50

True Weighting Matrix		T= 20				T= 30				T= 40				T= 80			
		Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max	Mean	STD	Min	Max
Wij = [(1/(N-1))-0.1, (1/(N-1))+0.1], , i <> j; otherwise Wij = 0	b1	1.00037	0.03322	0.90003	1.07567	0.99484	0.0277	0.91446	1.05168	1.00103	0.02247	0.94958	1.05674	0.99784	0.01746	0.95256	1.04275
	se(b1)	0.03258	0.00225	0.02874	0.04334	0.02635	0.00105	0.0243	0.02952	0.0227	0.00069	0.02141	0.02597	0.01595	0.00028	0.01525	0.01688
	b2	1.02831	0.20347	0.61797	1.77008	0.99511	0.13189	0.63133	1.47927	0.97695	0.1165	0.77513	1.54147	0.98023	0.06585	0.80412	1.13245
	se(b2)	0.14744	0.03182	0.07111	0.25853	0.11676	0.01796	0.07629	0.16947	0.09969	0.01507	0.06525	0.15914	0.06787	0.00715	0.04966	0.08569
	b3	1.00151	0.03303	0.92295	1.10933	0.99508	0.025	0.92585	1.04713	1.00244	0.02216	0.9478	1.05508	0.99795	0.01582	0.96255	1.03693
	se(b3)	0.03439	0.00611	0.02429	0.05662	0.02735	0.00365	0.01774	0.03889	0.02325	0.00262	0.01753	0.02972	0.01598	0.0012	0.0135	0.02122
	b4	0.06995	0.1909	-0.8132	0.46118	0.10418	0.11354	-0.2606	0.41203	0.1228	0.10076	-0.3259	0.29192	0.11829	0.05892	-0.0394	0.27021
	se(b4)	0.12953	0.03044	0.05874	0.2671	0.10195	0.01602	0.0694	0.15088	0.08701	0.01312	0.06261	0.12992	0.05949	0.00626	0.04513	0.0754
Wij = [(1/(N-1))-0.5, (1/(N-1))+0.5], , i <> j; otherwise Wij = 0	b1	1.00121	0.03683	0.90987	1.1041	1.00042	0.02984	0.92187	1.06946	0.99607	0.02562	0.9081	1.0604	0.99783	0.01926	0.94989	1.04665
	se(b1)	0.0353	0.00199	0.0314	0.04591	0.02862	0.00113	0.02619	0.03298	0.02459	0.00074	0.02305	0.02762	0.01726	0.00034	0.01645	0.01799
	b2	1.04272	0.2273	0.68685	1.98602	1.02103	0.15305	0.73984	1.74779	1.01633	0.13539	0.732	1.41984	0.98997	0.07457	0.82711	1.17401
	se(b2)	0.15509	0.03624	0.07226	0.31529	0.12356	0.02284	0.05828	0.21274	0.10698	0.01608	0.07462	0.15175	0.0719	0.00746	0.05296	0.08787
	b3	1.00464	0.03933	0.9113	1.12749	1.00214	0.02936	0.93371	1.07624	1.00465	0.02469	0.93812	1.07584	0.99634	0.01775	0.95319	1.04398
	se(b3)	0.03598	0.00597	0.0242	0.05455	0.02975	0.00405	0.02246	0.04934	0.02512	0.00294	0.01928	0.03432	0.01729	0.00119	0.01475	0.02238
	b4	0.05797	0.20596	-0.6542	0.37508	0.08029	0.13973	-0.5376	0.36281	0.08103	0.13156	-0.3331	0.35304	0.10924	0.07431	-0.1501	0.26991
	se(b4)	0.13604	0.03219	0.06534	0.25481	0.10804	0.01998	0.05542	0.18135	0.09381	0.01451	0.06478	0.13489	0.06293	0.00683	0.04973	0.082
Wij = u[-0.5, 0.5], , i <> j; otherwise Wij = 0	b1	1.00613	0.0359	0.9023	1.07114	0.99728	0.0292	0.93952	1.07975	0.99492	0.02371	0.92182	1.04437	1.00145	0.0165	0.96135	1.03958
	se(b1)	0.03526	0.00206	0.03159	0.04223	0.02834	0.00098	0.02631	0.03152	0.02455	0.00069	0.02289	0.02677	0.01722	0.00031	0.01646	0.01807
	b2	1.08248	0.20883	0.73896	2.13275	1.06221	0.17552	0.70767	1.58741	1.03694	0.10989	0.84022	1.3249	1.03076	0.08925	0.84953	1.35046
	se(b2)	0.15048	0.03034	0.07723	0.21874	0.12309	0.02317	0.08383	0.17751	0.1055	0.01482	0.07195	0.14581	0.07158	0.00778	0.05579	0.0909
	b3	0.9978	0.03629	0.91814	1.09308	0.99981	0.02961	0.913	1.0737	0.99614	0.02712	0.92914	1.05945	0.99829	0.01749	0.95826	1.04044
	se(b3)	0.03601	0.00551	0.02469	0.0501	0.02907	0.00341	0.02238	0.03747	0.02512	0.00301	0.01943	0.03296	0.01755	0.00147	0.01401	0.0224
	b4	-0.0893	0.22349	-1.3185	0.23551	-0.0618	0.181	-0.6428	0.29579	-0.0367	0.11614	-0.3493	0.20392	-0.0373	0.09574	-0.3393	0.14235
	se(b4)	0.14771	0.03074	0.08006	0.2359	0.11989	0.02241	0.07721	0.17863	0.10235	0.0143	0.07388	0.14314	0.06981	0.00726	0.05222	0.08746

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